

# Internet Vision

## Lecture 14

With many slides from: N. Snavely, L. van Ahn, J. Hays, A. Efros

# What is Internet Vision?

- Vast majority of data on Internet is in form of images/video
- Lots of unique applications of Computer Vision in this setting
- Also a very useful tool for vision researchers
  - Get labels for images

# The Internet as source of labor

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## Make Money by working on HITs

HITs - *Human Intelligence Tasks* - are individual tasks that you work on. [Find HITs now.](#)

### As a Mechanical Turk Worker you:

- Can work from home
- Choose your own work hours
- Get paid for doing good work



# LabelMe

LabelMe



Zoom



Erase



Help



Make 3D



Upload image



Show me another image

[Sign in \(why?\)](#)

There are **773284** labelled objects

## Polygons in this image

(IMG, XML)

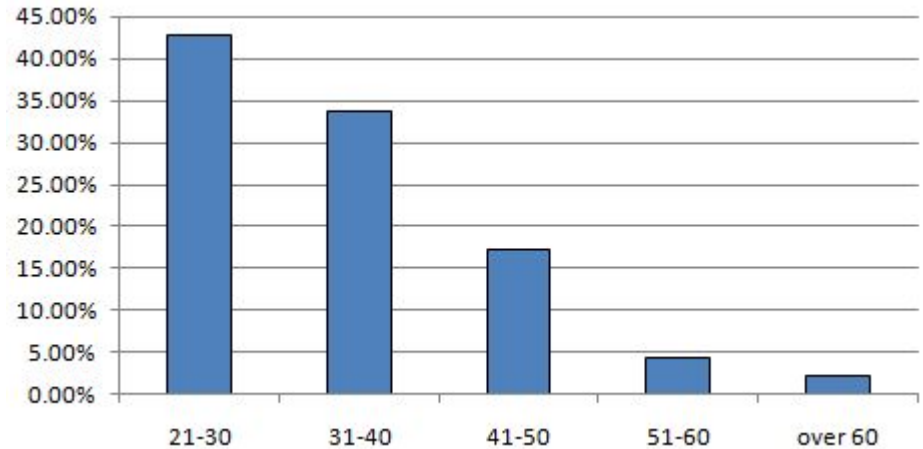
[tree](#)  
[tree](#)  
[house](#)  
[sidewalk](#)  
[bicycle](#)  
[Sign](#)  
[top of tree](#)  
[ma](#)  
[car](#)  
[road](#)  
[sky](#)  
[sign](#)  
[sign](#)  
[door](#)



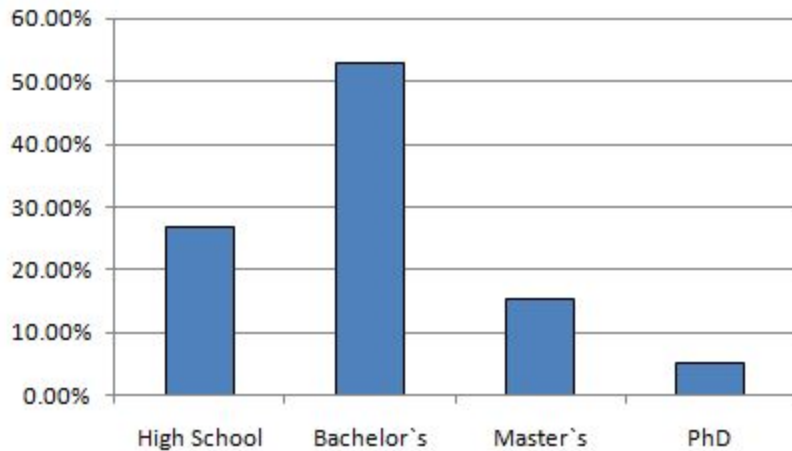


# Mechanical Turk – Demographics

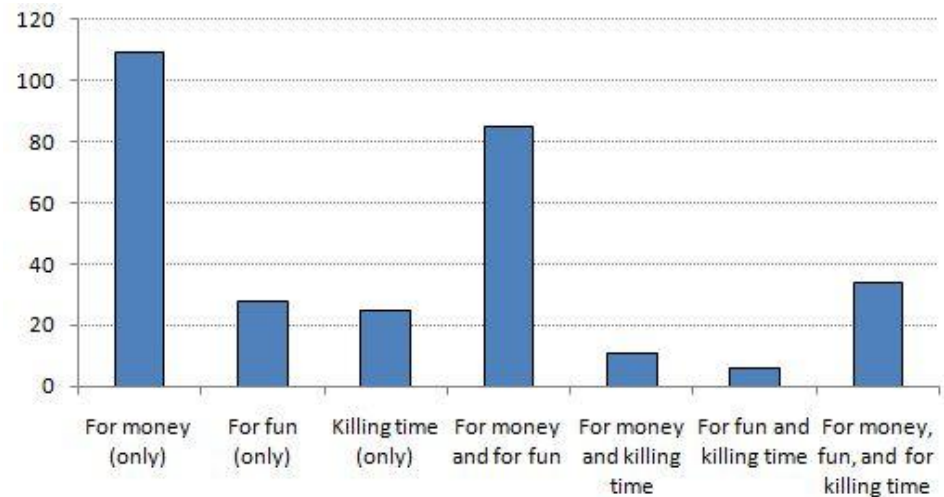
United States	76.25%
India	8.03%
United Kingdom	3.34%
Canada	2.34%



Age distribution



Age distribution



Motivation

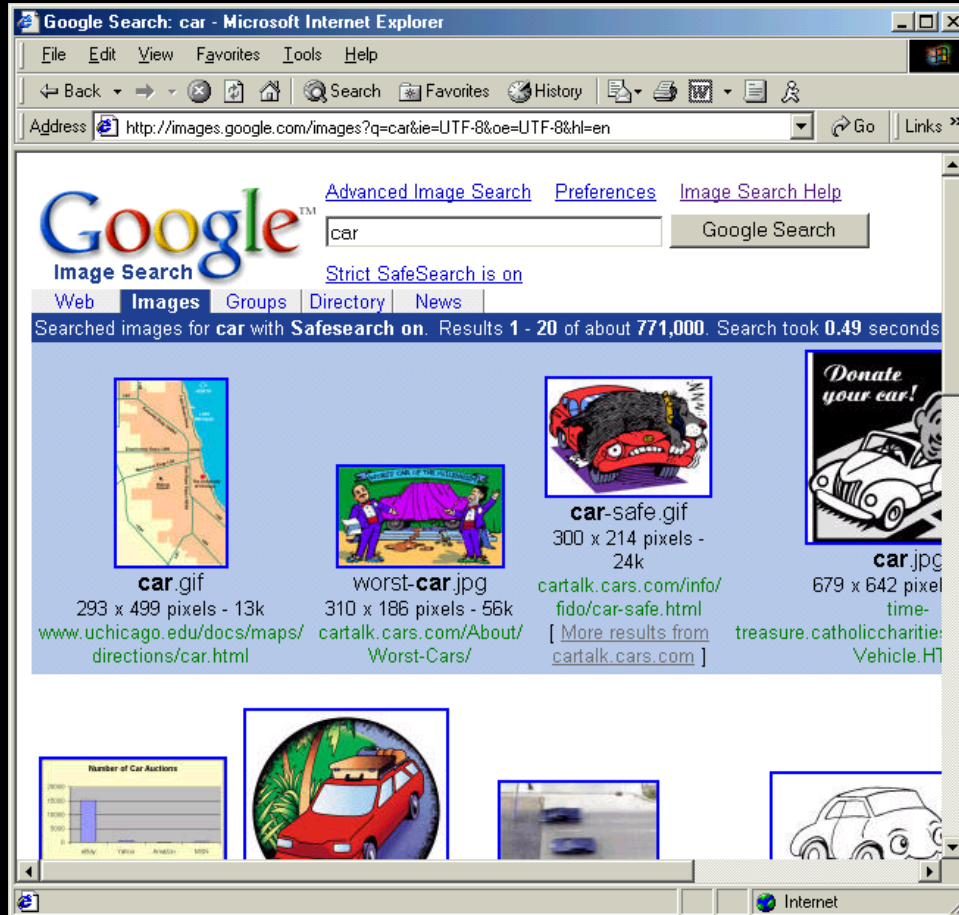
# **LABELING IMAGES WITH WORDS**



**MARTHA STEWART**  
**FLOWERS**  
**SUPER EVIL**

**STILL AN OPEN PROBLEM**

# IMAGE SEARCH ON THE WEB



**USES FILENAMES  
AND HTML TEXT**

# THE ESP GAME

TWO-PLAYER ONLINE GAME

PARTNERS DON'T KNOW EACH OTHER  
AND CAN'T COMMUNICATE

OBJECT OF THE GAME:  
**TYPE THE SAME WORD**

THE ONLY THING IN COMMON IS  
**AN IMAGE**

# THE ESP GAME

PLAYER 1



GUESSING: **CAR**  
GUESSING: **HAT**  
GUESSING: **KID**  
SUCCESS!  
**YOU AGREE ON CAR**

PLAYER 2



GUESSING: **BOY**  
GUESSING: **CAR**  
SUCCESS!  
**YOU AGREE ON CAR**

**0:46**  
Time Left

# The ESP Game

**0220**  
score

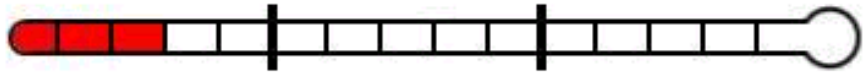


**Taboo Words**  
HAT  
SUNGLASSES

**Your Guesses**  
MAN  
PERSON  
GUY

Type your next guess:

Pass



# **THE ESP GAME IS FUN**

**4.1 MILLION LABELS** WITH 23,000 PLAYERS

THERE ARE MANY PEOPLE THAT PLAY  
**OVER 20 HOURS A WEEK**



# SAMPLE LABELS



BEACH  
CHAIRS  
SEA  
SEA  
PEOPLE  
MAN  
WOMAN  
PLANT  
OCEAN  
TALKING  
WATER  
PORCH

# REVEALING IMAGES

GUESSER

**BRAISH**

GUESS

REVEALER



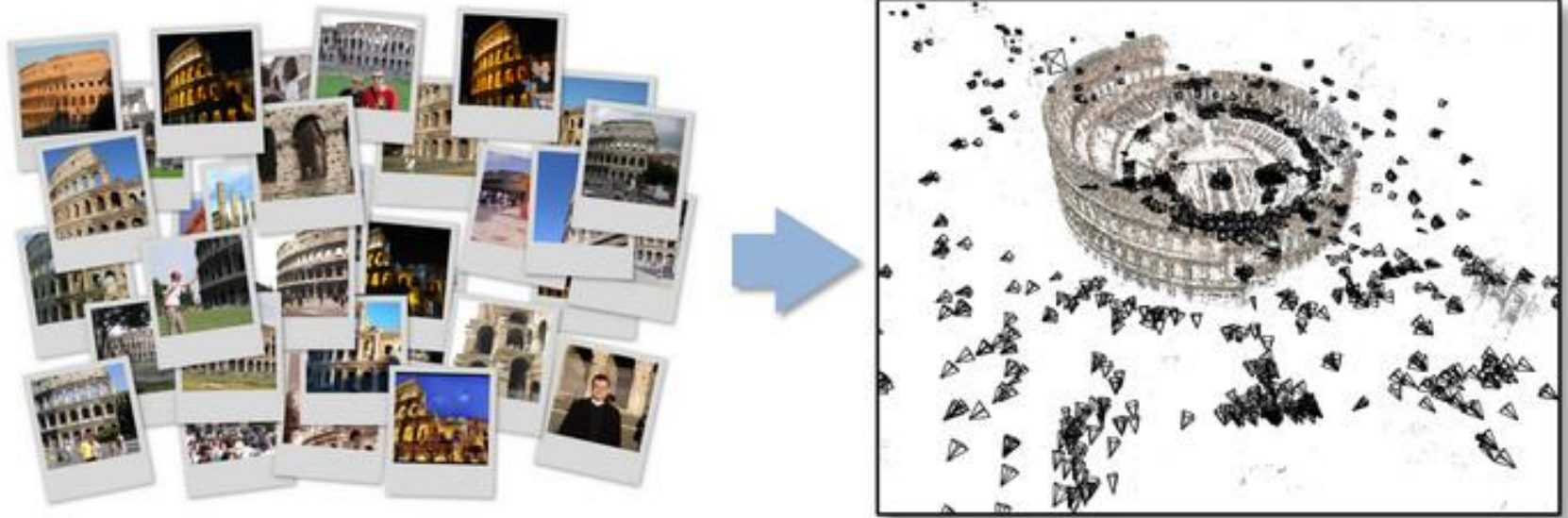
CAR

**BRAISH**

PARTNER'S  
GUESS

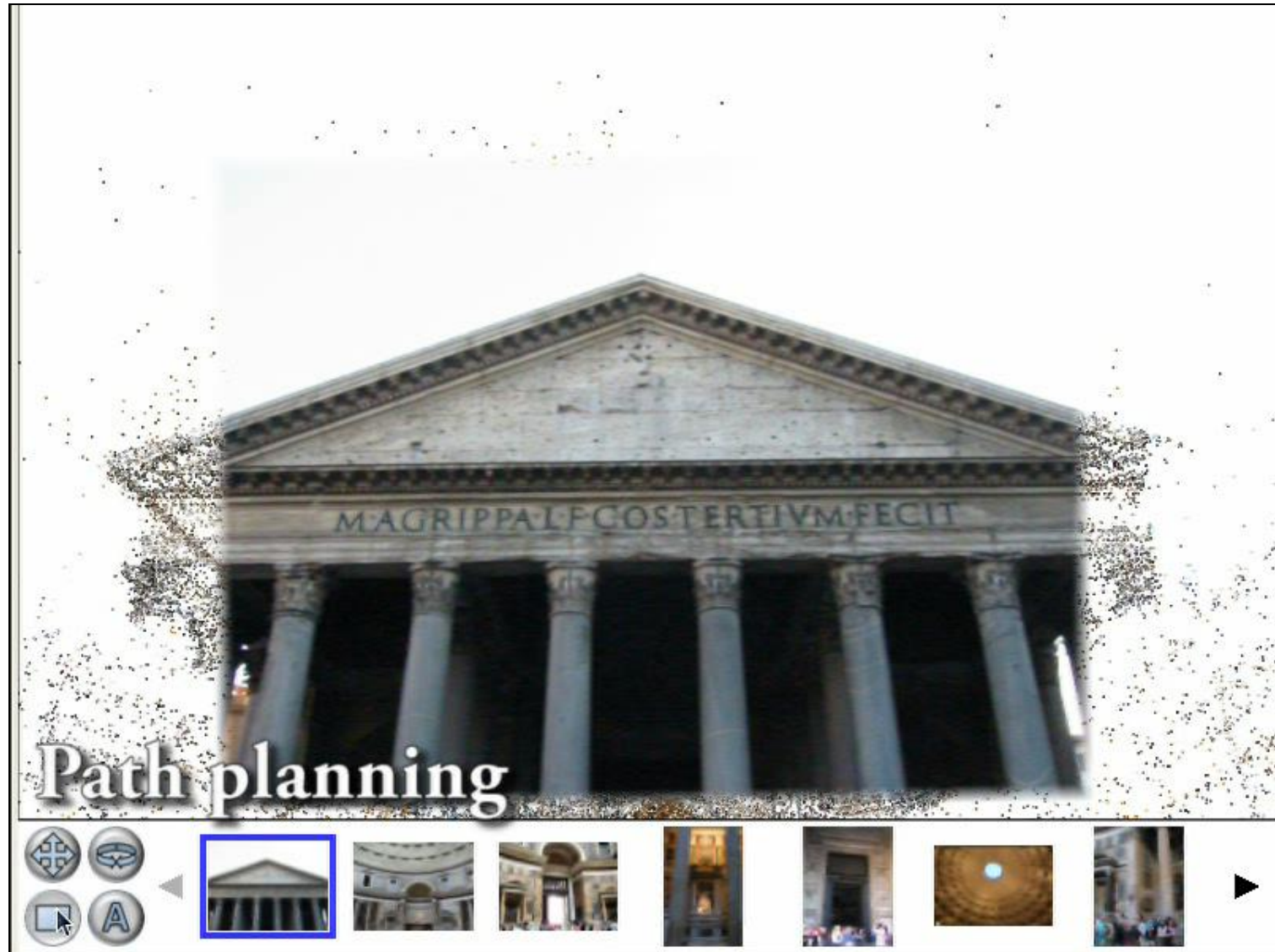
# Photo Collections

- Phototourism / Photosynth
  - Snavely, Szeliski and Seitz (Siggraph 2006)



# Scene exploration

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# Mapping the World's Photos (35 million)



# Mapping the World's Photos





# Camera calibration

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**"Priors for Large Photo Collections and What They Reveal about Cameras ,"**  
S. Kuthirummal, A. Agarwala, D. B Goldman, and S. K. Nayar,  
European Conference on Computer Vision, 2010



# Leveraging Huge Data

- What if we had millions or billions of images?
  - Facebook has  $O(10^{10})$  images (10 Billion)
  - Roughly a lifetime of visual experience (5 glances/sec)
- What kind of new algorithms could we apply?
  - Brute Force methods

# Scene Completion Using Millions of Photographs

James Hays and Alexei A. Efros  
Carnegie Mellon University







Efros and Leung result





Criminisi et al. result



Criminisi et al. result





# Scene Matching for Image Completion





Change **Alley** Aerial Plaza with its ...  
300 x 400 - 21k  
[en.wikipedia.org](http://en.wikipedia.org)



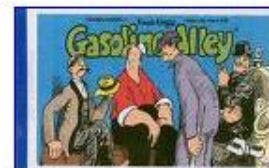
The Printer's **Alley** sign looking ...  
679 x 450 - 469k - jpg  
[franklin.thefuntimesguide.com](http://franklin.thefuntimesguide.com)



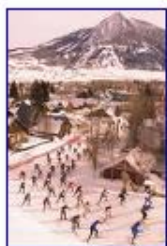
Looking west past Printers **Alley**.  
679 x 450 - 464k - jpg  
[franklin.thefuntimesguide.com](http://franklin.thefuntimesguide.com)



More Bubble Gum **Alley** photos can be ...  
764 x 591 - 33k - gif  
[www.localinks.com](http://www.localinks.com)



Gasoline **Alley** gang  
692 x 430 - 177k - jpg  
[newcritics.com](http://newcritics.com)



2007 **Alley** Loop Sponsors  
300 x 453 - 51k - jpg  
[www.cbnordic.org](http://www.cbnordic.org)



Change **Alley** : interior  
550 x 413 - 98k  
[infopedia.nlb.gov.sg](http://infopedia.nlb.gov.sg)



Earl G. **Alley** ...  
321 x 383 - 19k - jpg  
[www.msstate.edu](http://www.msstate.edu)



Gun **Alley** 8.5x11 Full Color Ink Wash ...  
390 x 301 - 14k - jpg  
[www.rorschachentertainment.com](http://www.rorschachentertainment.com)



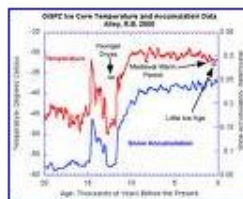
Grace Court **Alley**  
732 x 549 - 98k - jpg  
[www.bridgeandtunnelclub.com](http://www.bridgeandtunnelclub.com)



Grace Court **Alley**  
732 x 549 - 80k - jpg  
[www.bridgeandtunnelclub.com](http://www.bridgeandtunnelclub.com)



panoramic photo of Alligator **Alley**  
4902 x 460 - 1048k - jpg  
[sflwww.er.usgs.gov](http://sflwww.er.usgs.gov)



Richard B. **Alley**  
450 x 361 - 29k - gif  
[www.ncdc.noaa.gov](http://www.ncdc.noaa.gov)



Also, Chicken **Alley** is reported to ...  
450 x 337 - 82k  
[phidoux.typepad.com](http://phidoux.typepad.com)



Ego **Alley**  
500 x 375 - 48k - jpg  
[dc.about.com](http://dc.about.com)



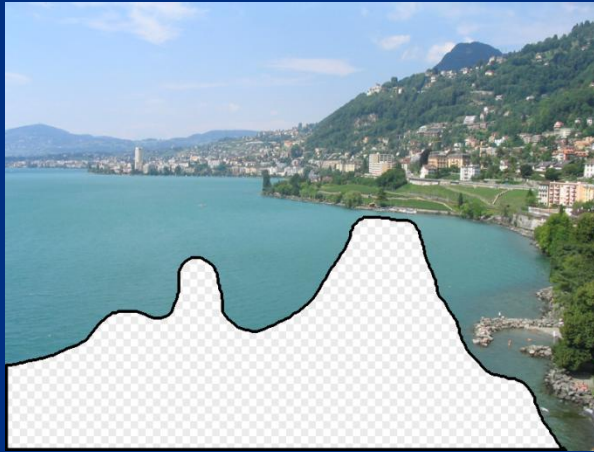




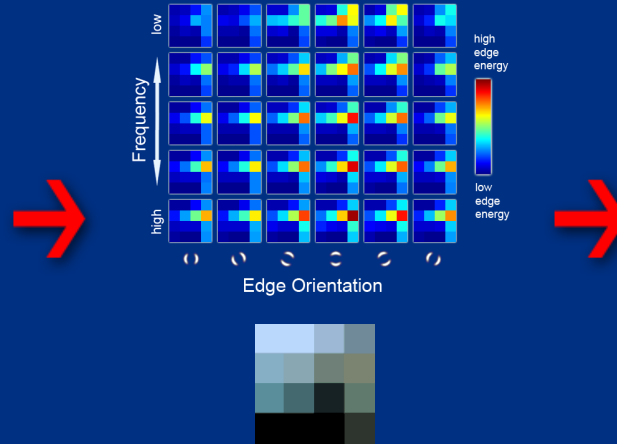


Scene Completion Result

# The Algorithm



Input image



Scene Descriptor



Image Collection



20 completions



Context matching  
+ blending



200 matches

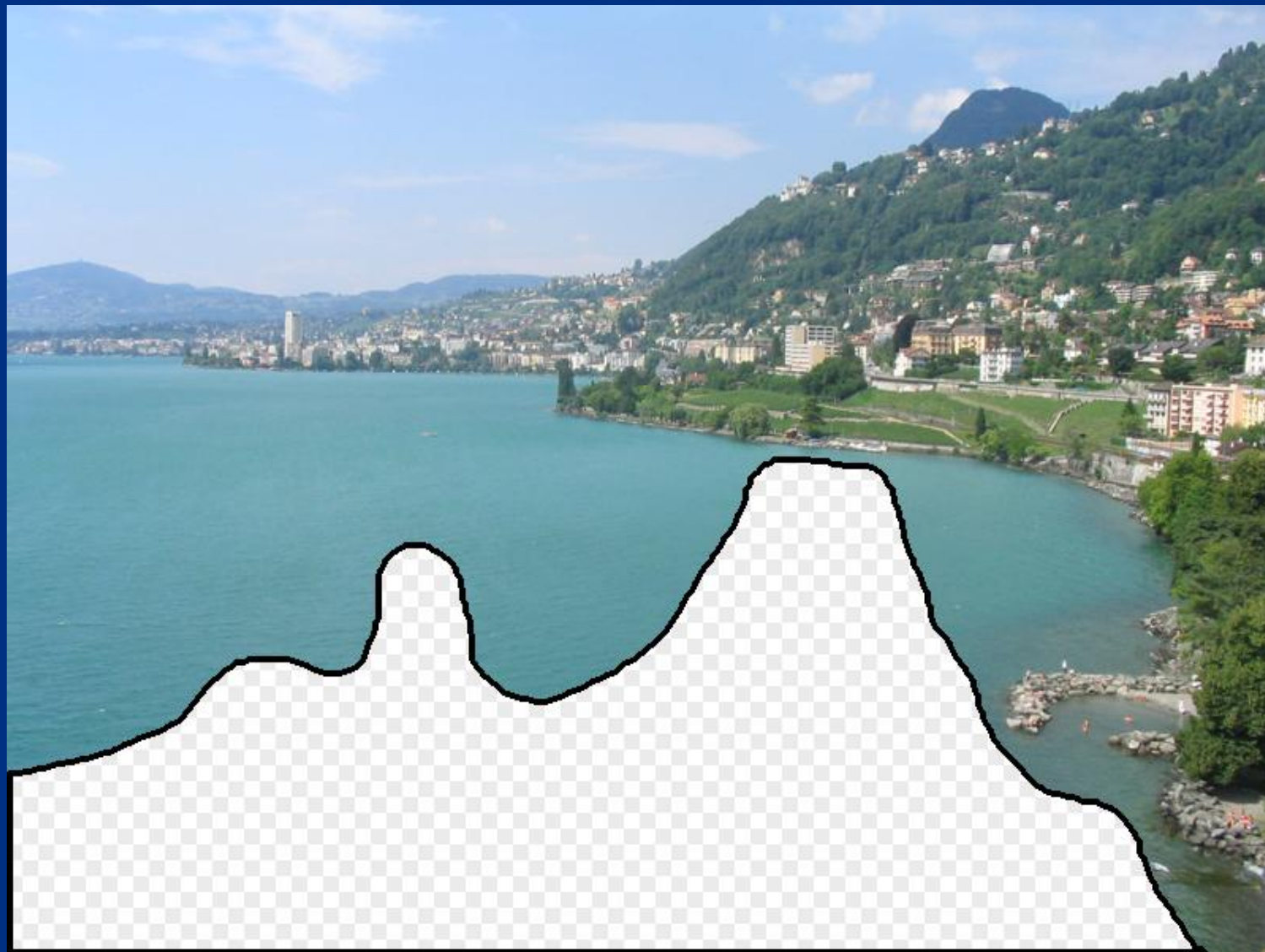
# Data

We downloaded 2.3 Million unique images from Flickr groups and keyword searches.

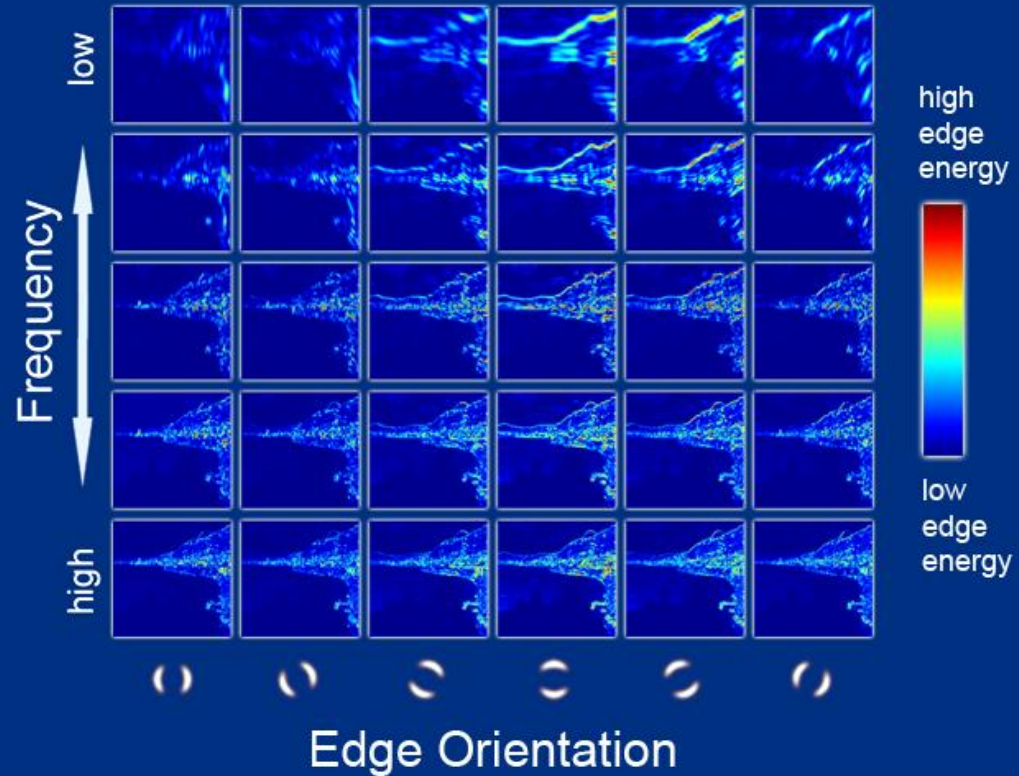
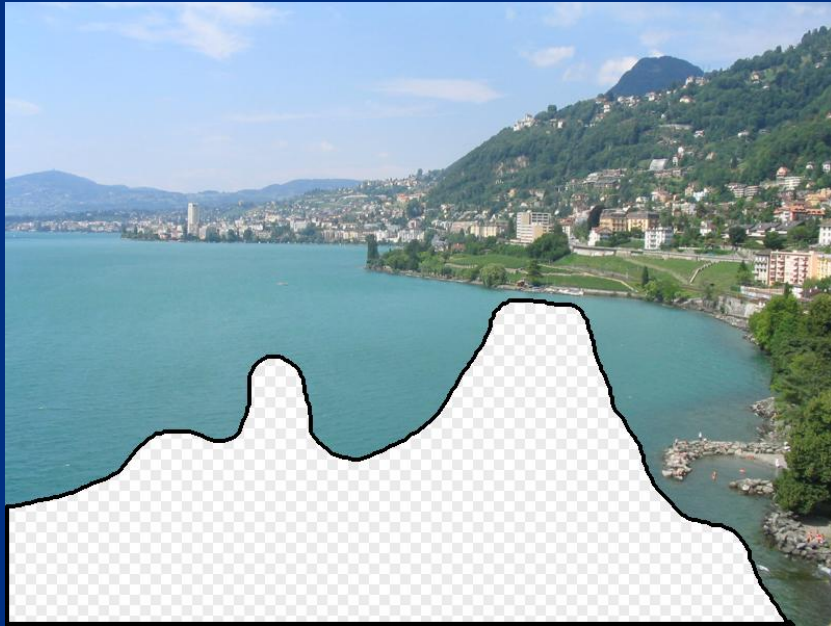




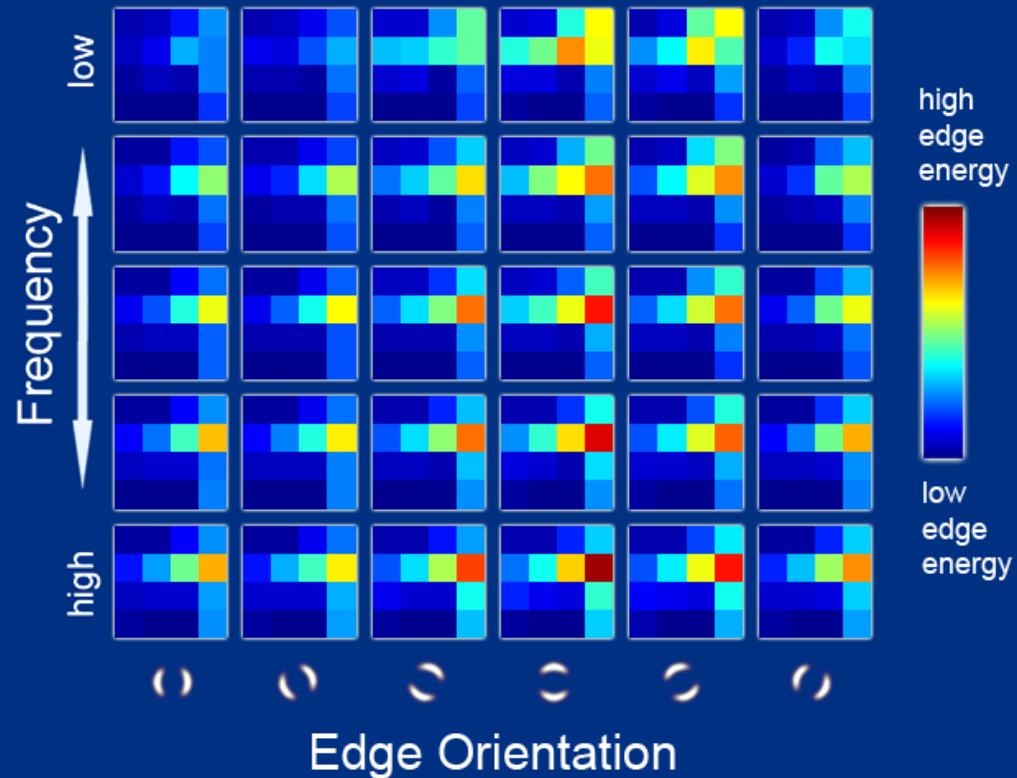
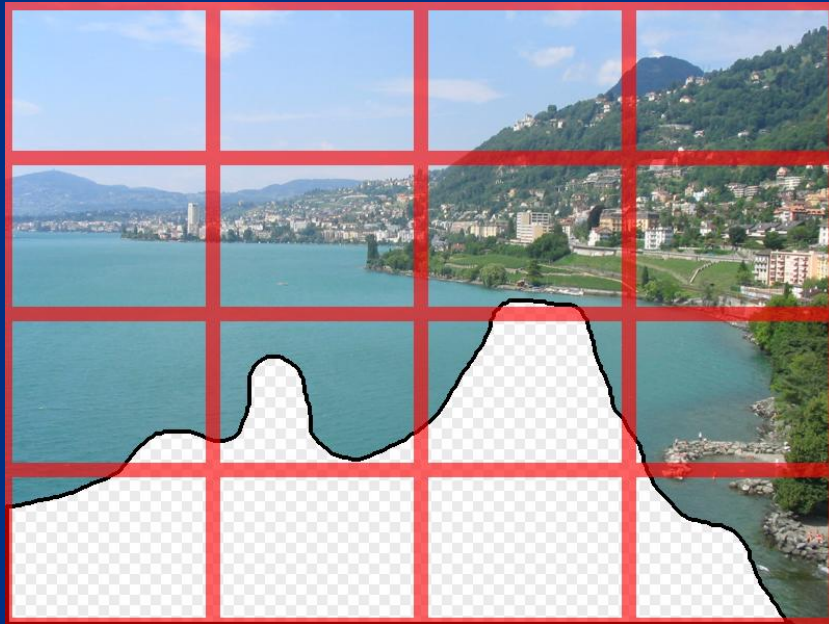
# Scene Matching



# Scene Descriptor

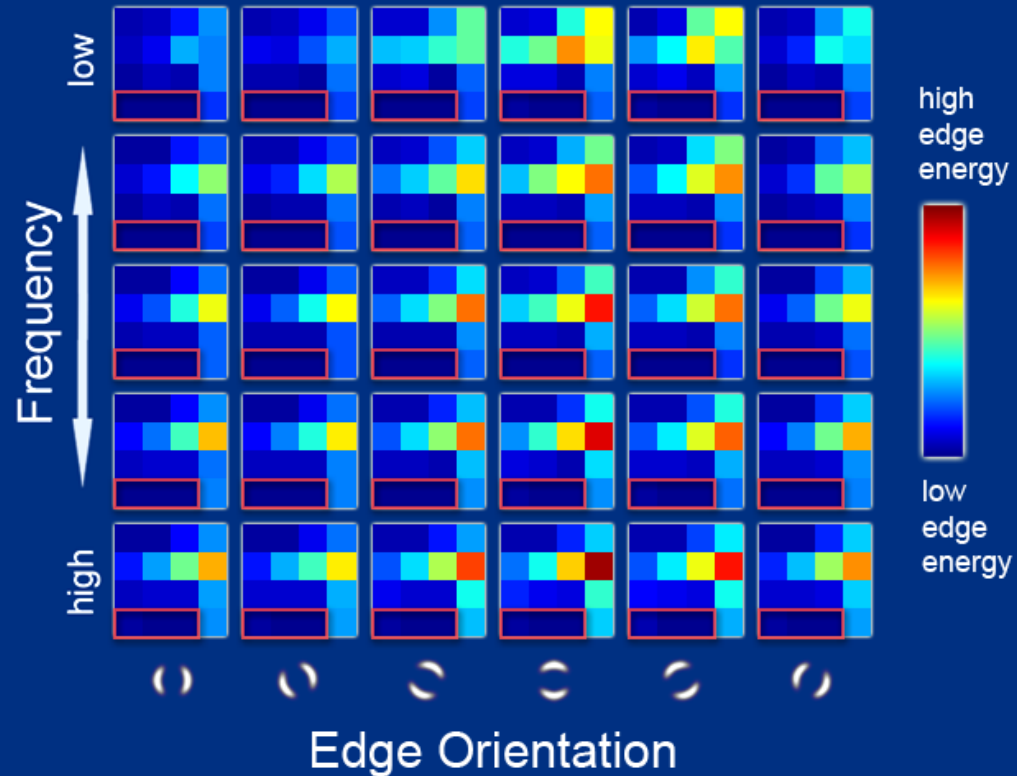
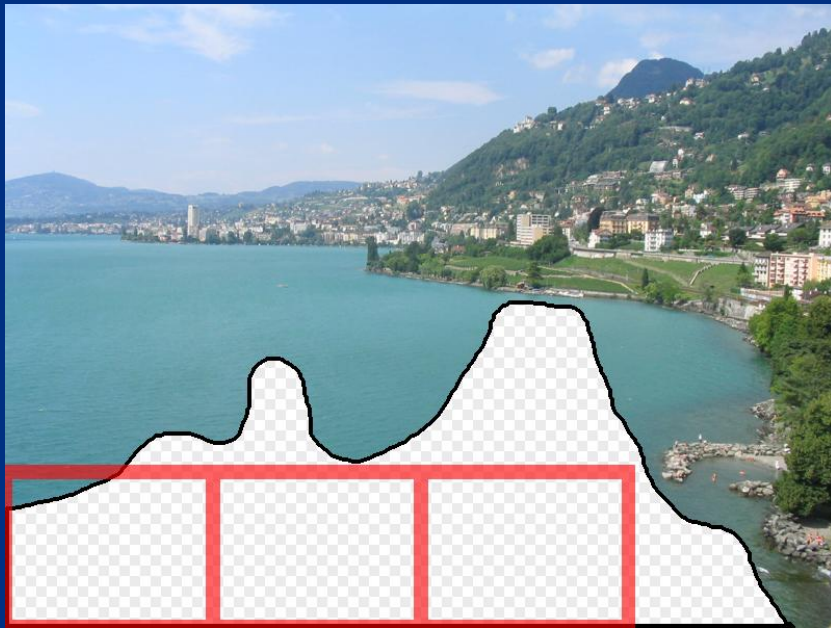


# Scene Descriptor



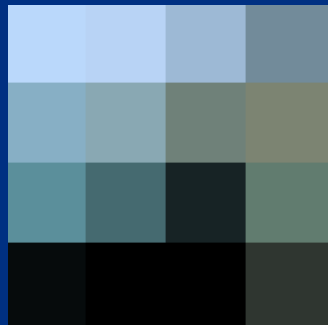
Gist scene descriptor  
(Oliva and Torralba 2001)

# Scene Descriptor

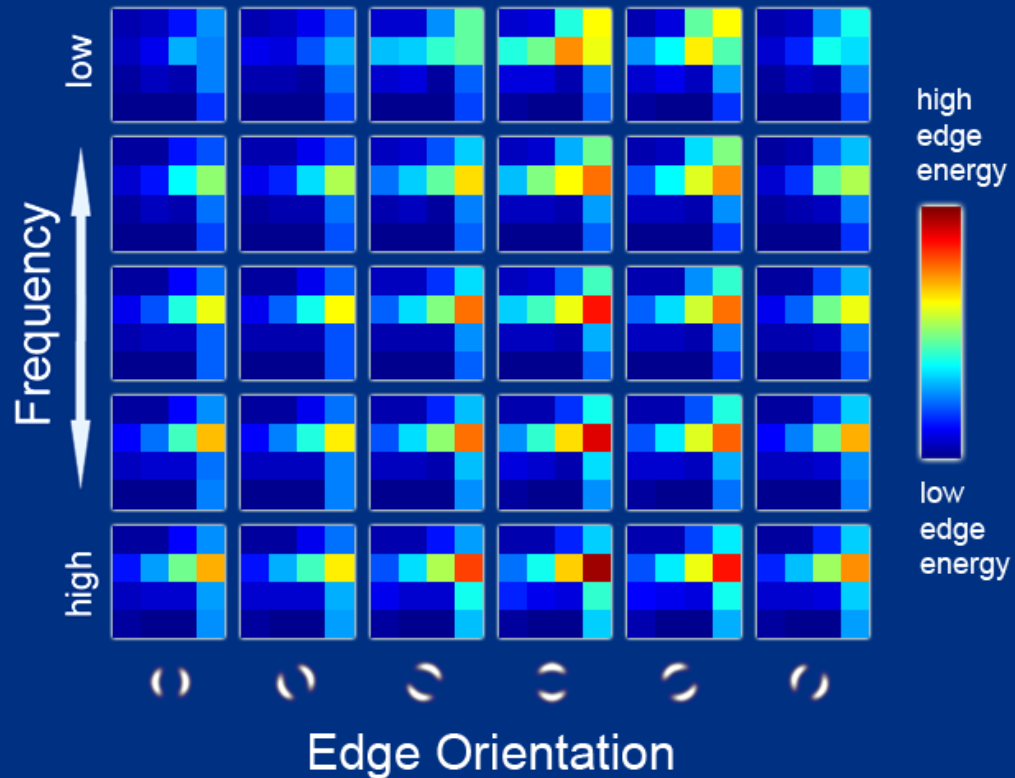


Gist scene descriptor  
(Oliva and Torralba 2001)

# Scene Descriptor



+

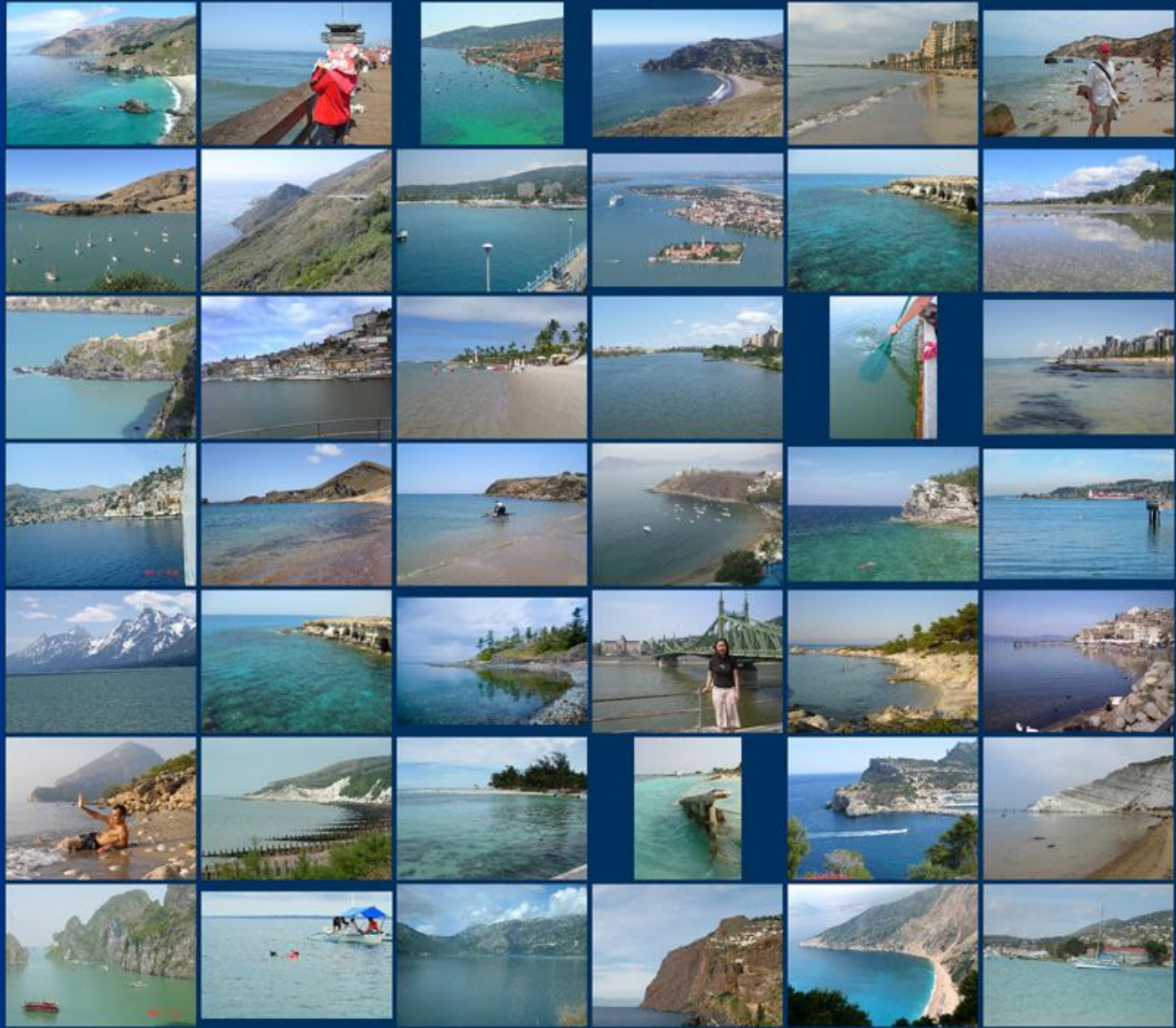
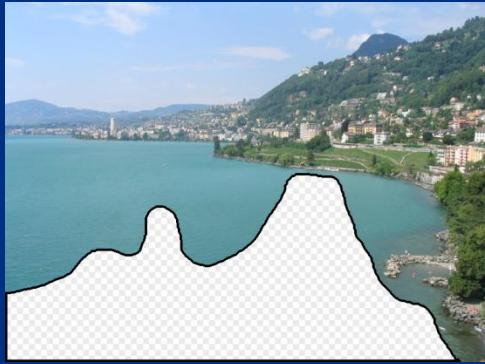


Gist scene descriptor  
(Oliva and Torralba 2001)



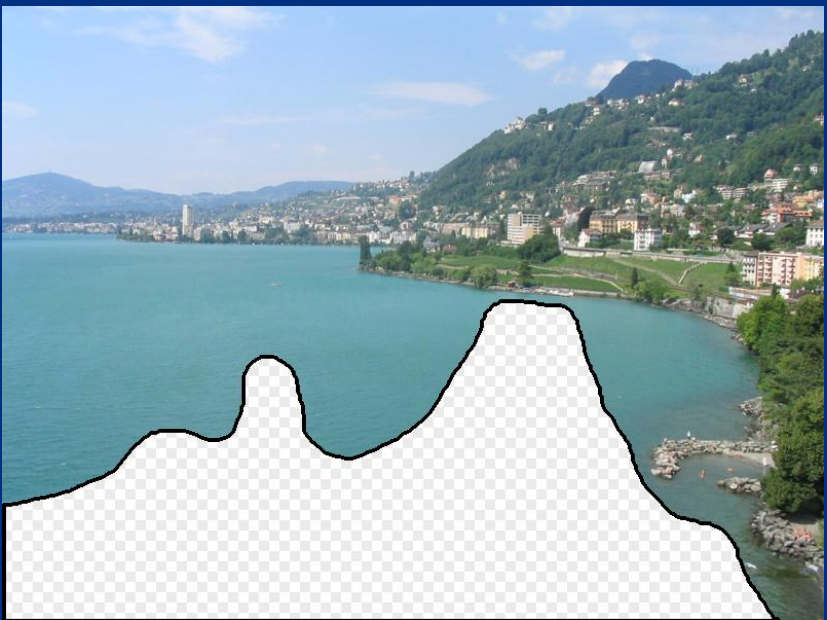






... 200 total

# Context Matching





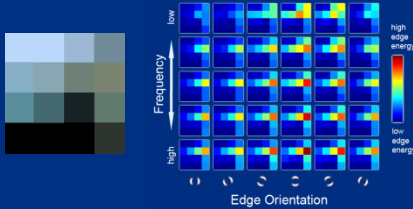






# Result Ranking

We assign each of the 200 results a score which is the sum of:



The scene matching distance



The context matching distance  
(color + texture)



The graph cut cost

# Top 20 Results















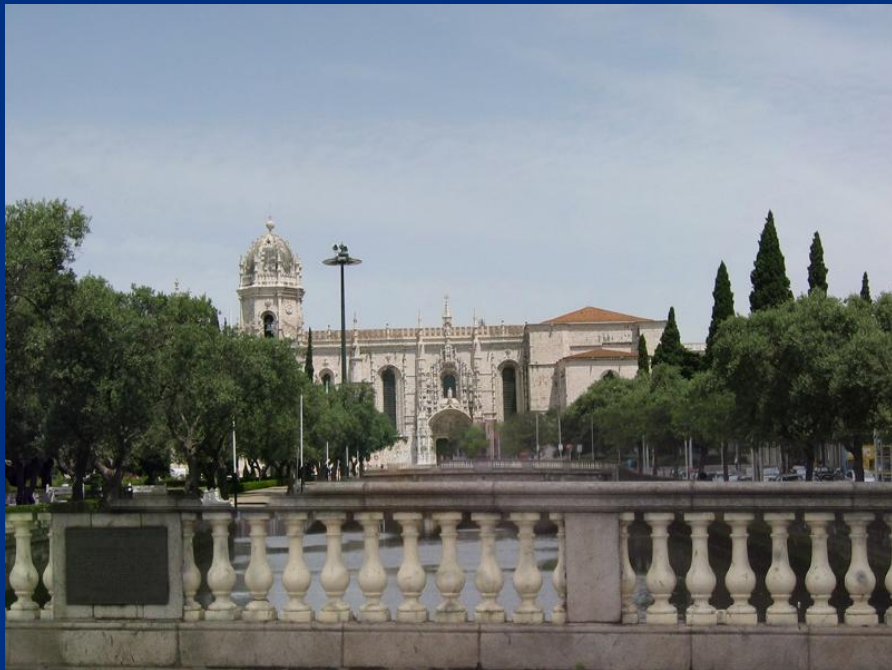
























... 200 scene matches





... 200 scene matches

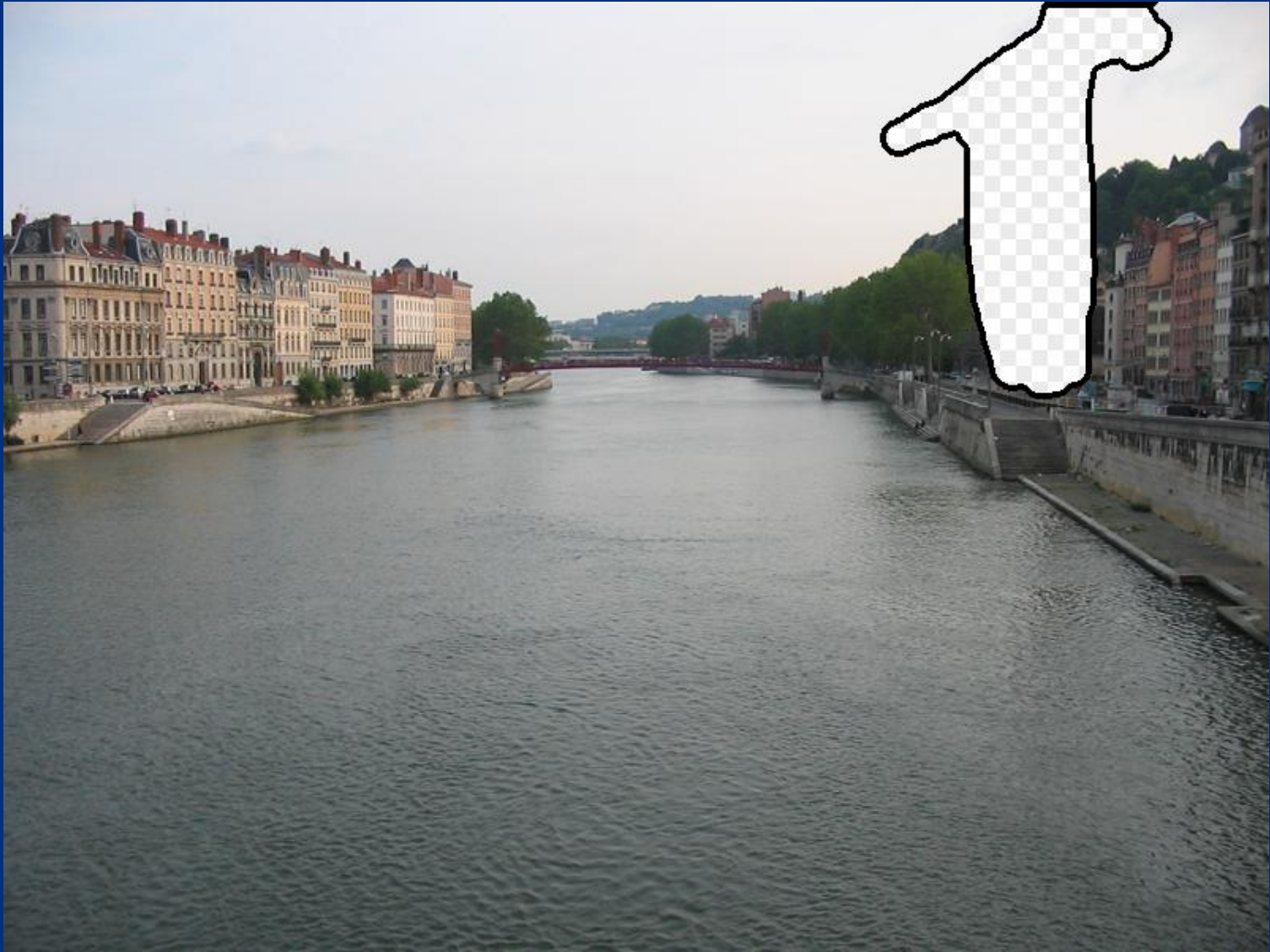






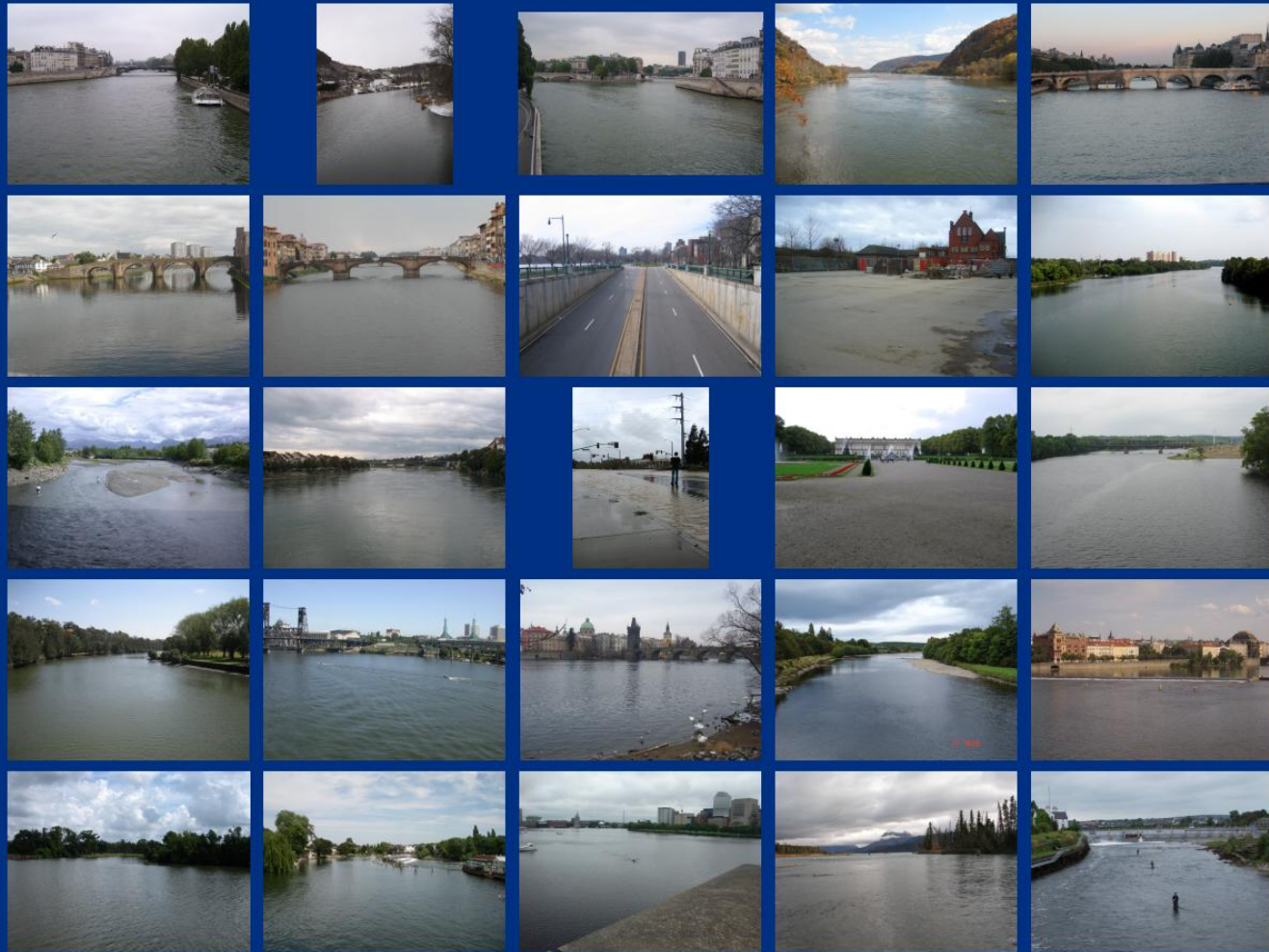
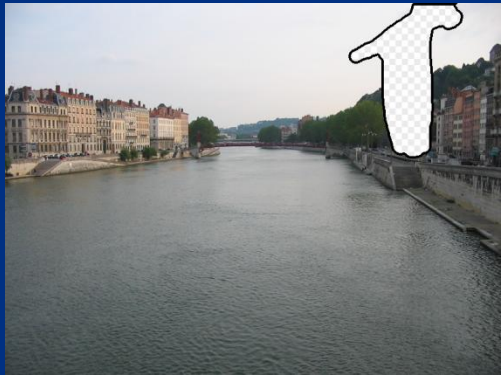




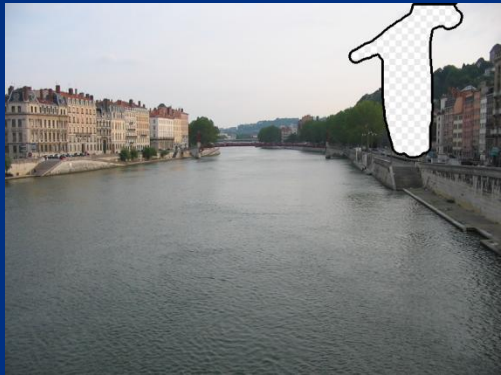






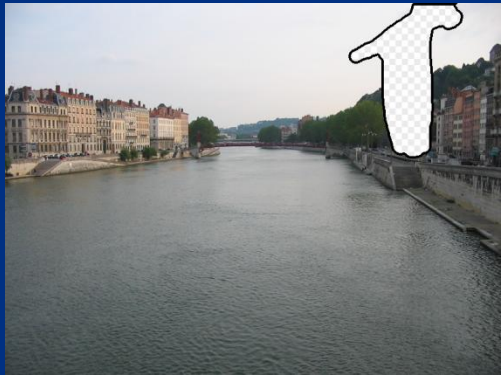


... 200 scene matches



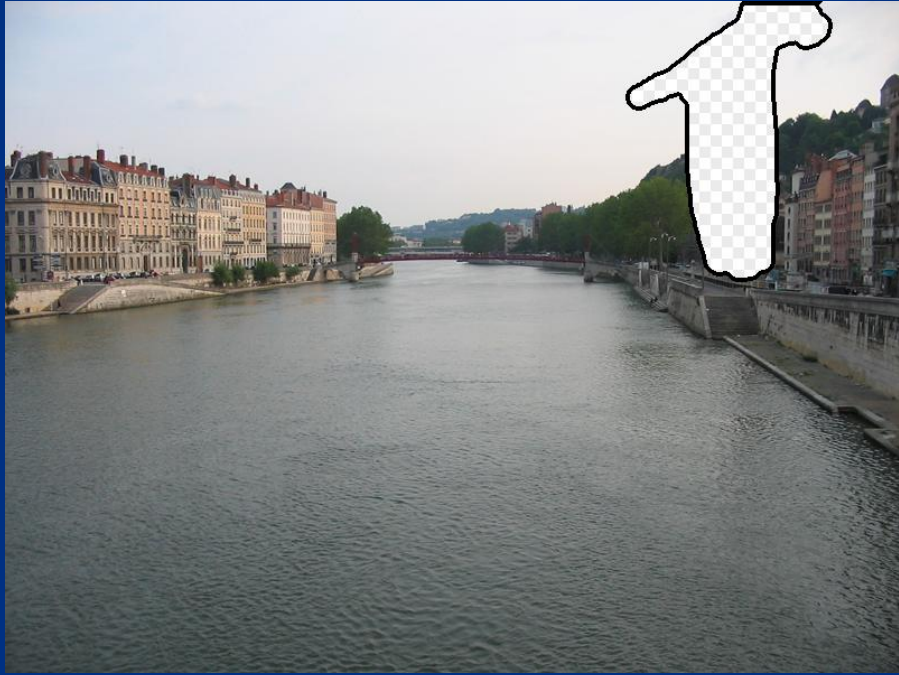
... 200 scene matches





... 200 scene matches











七五三  
神社  
入口



















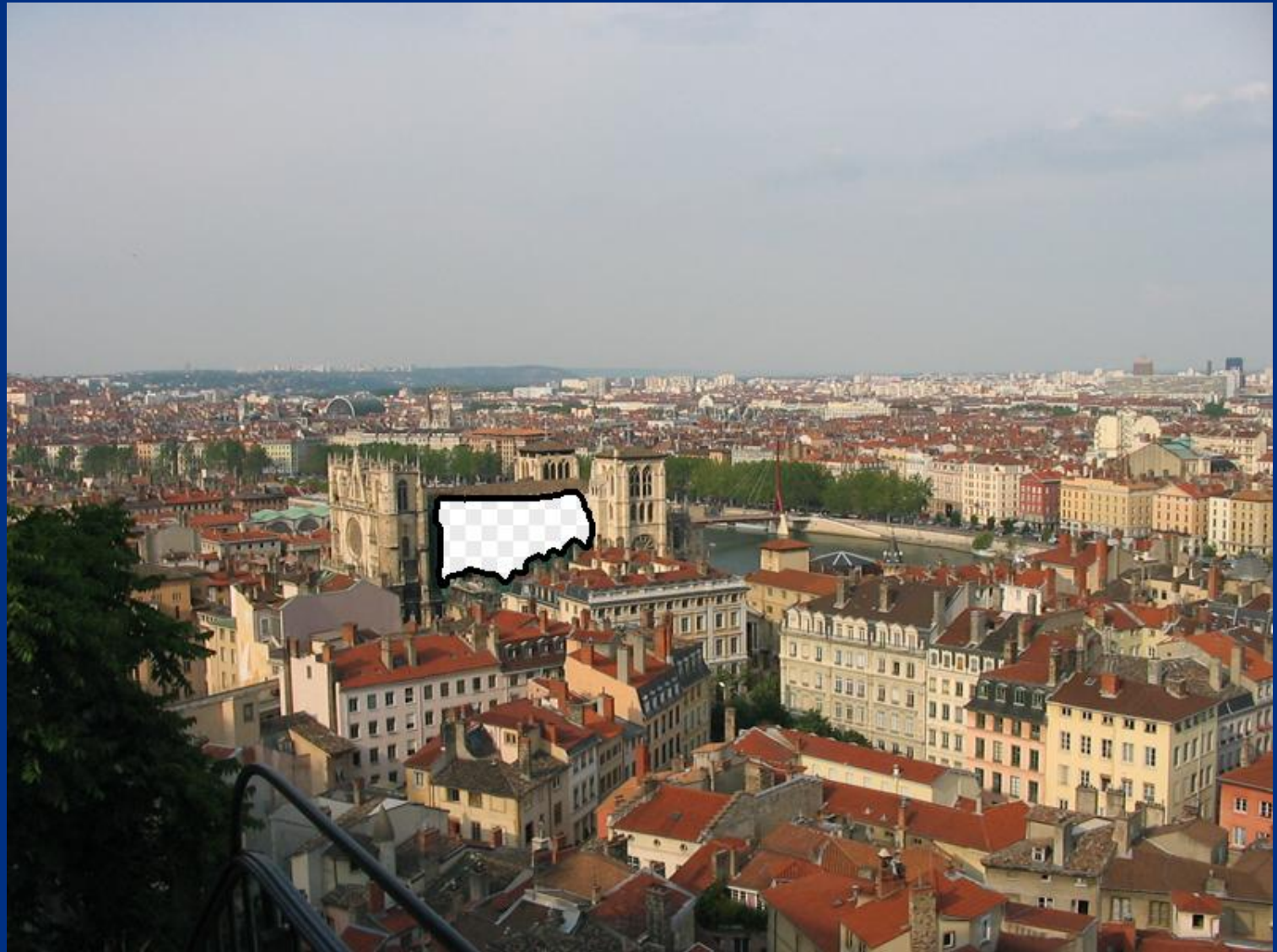






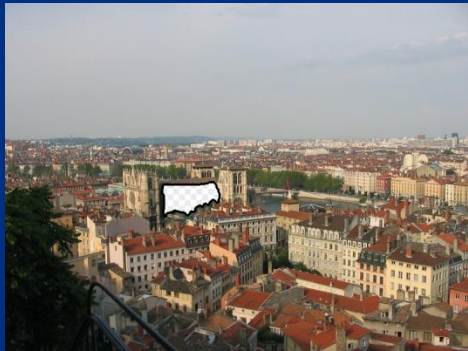












... 200 scene matches









# Failures

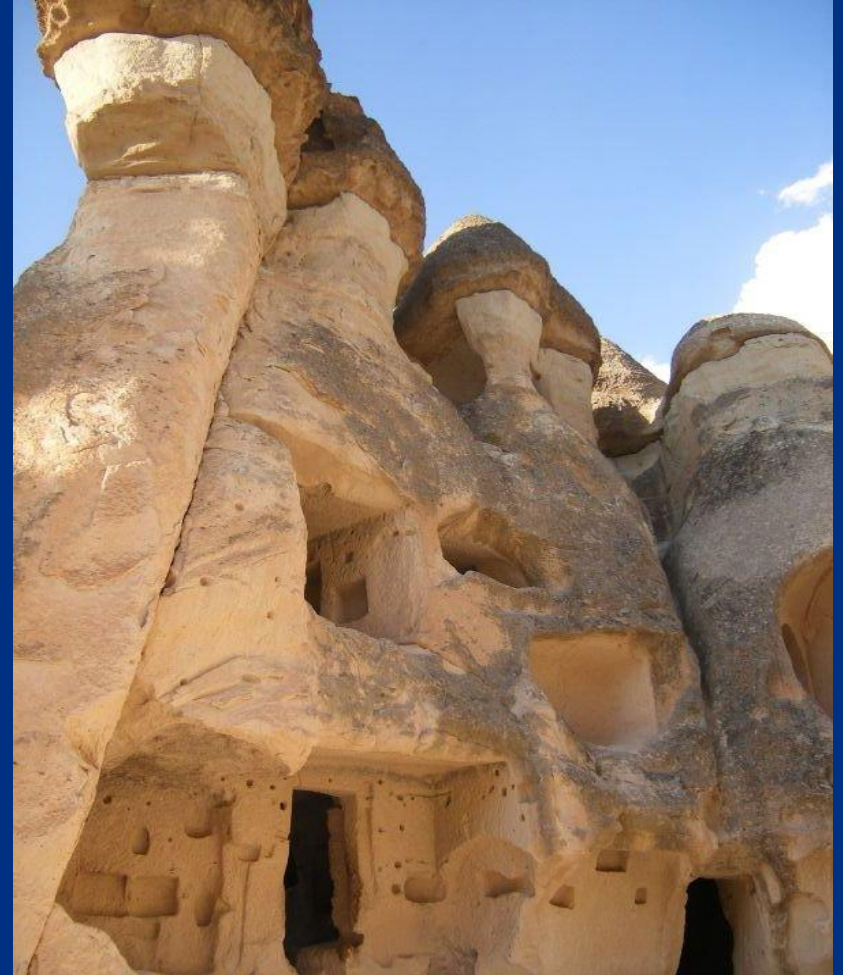


# Failures





# Failures



# Failures

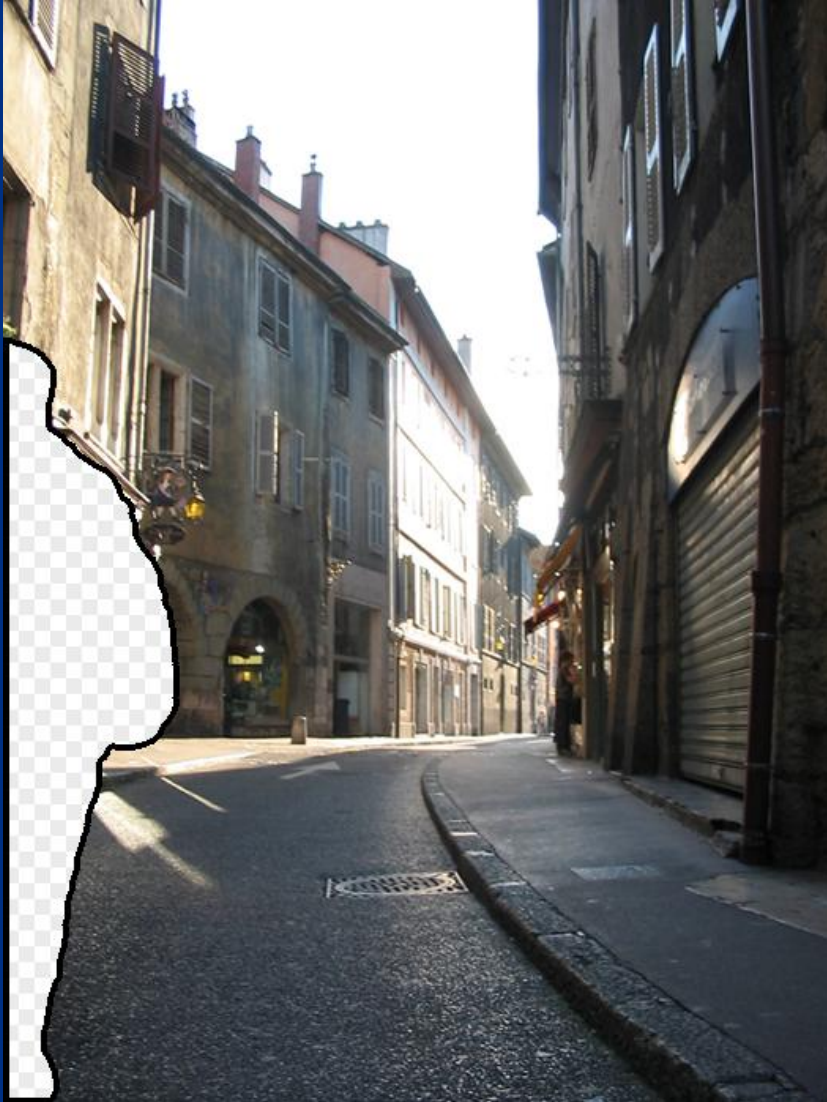


# Failures

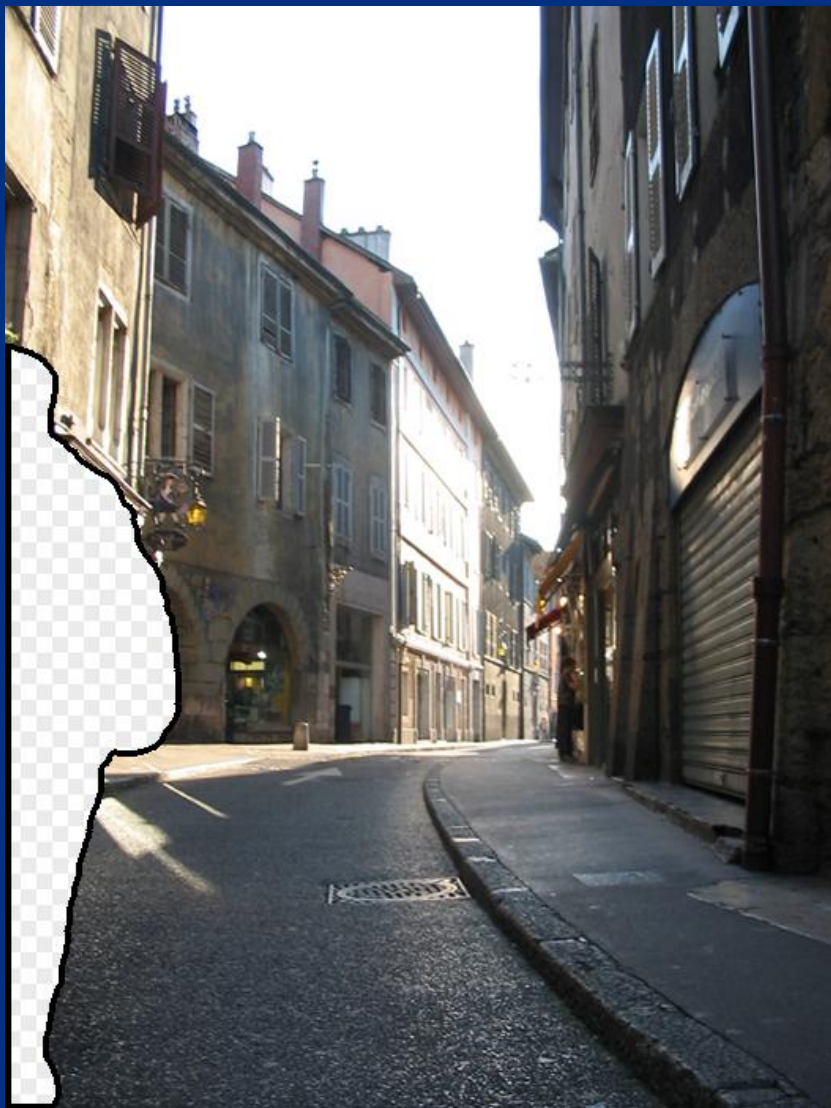




# Failures

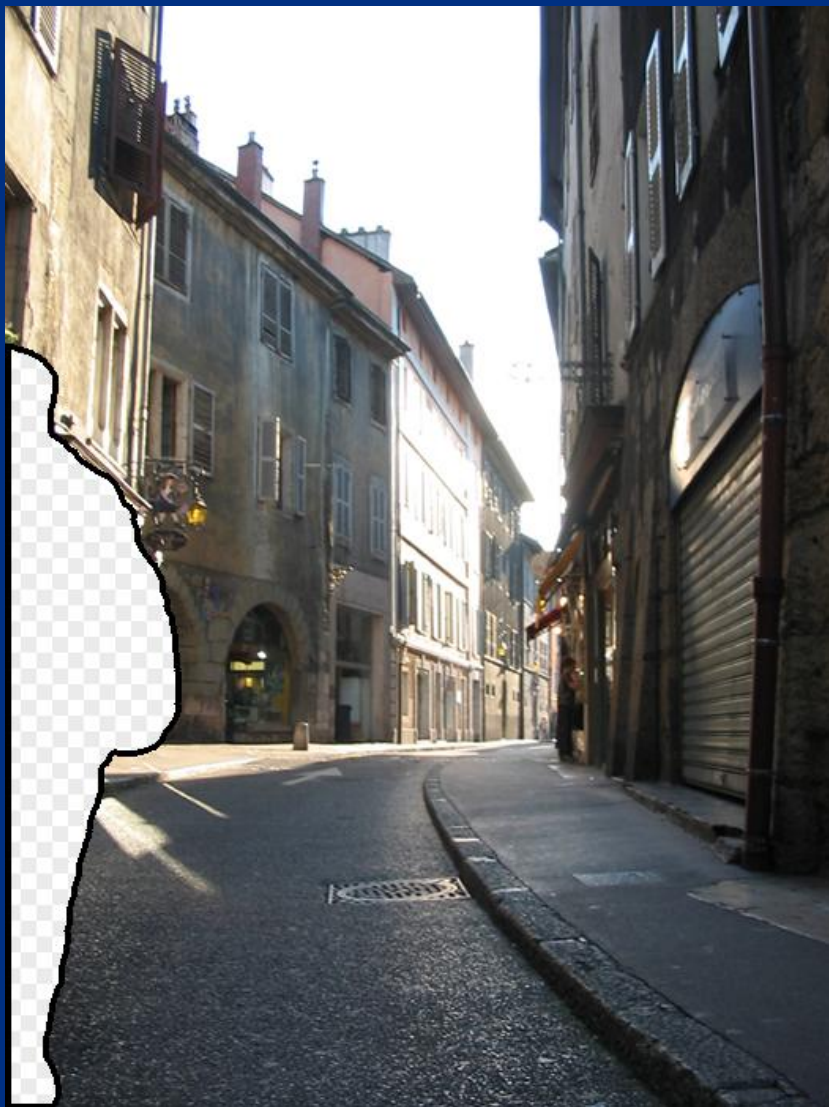


# Failures





# Failures

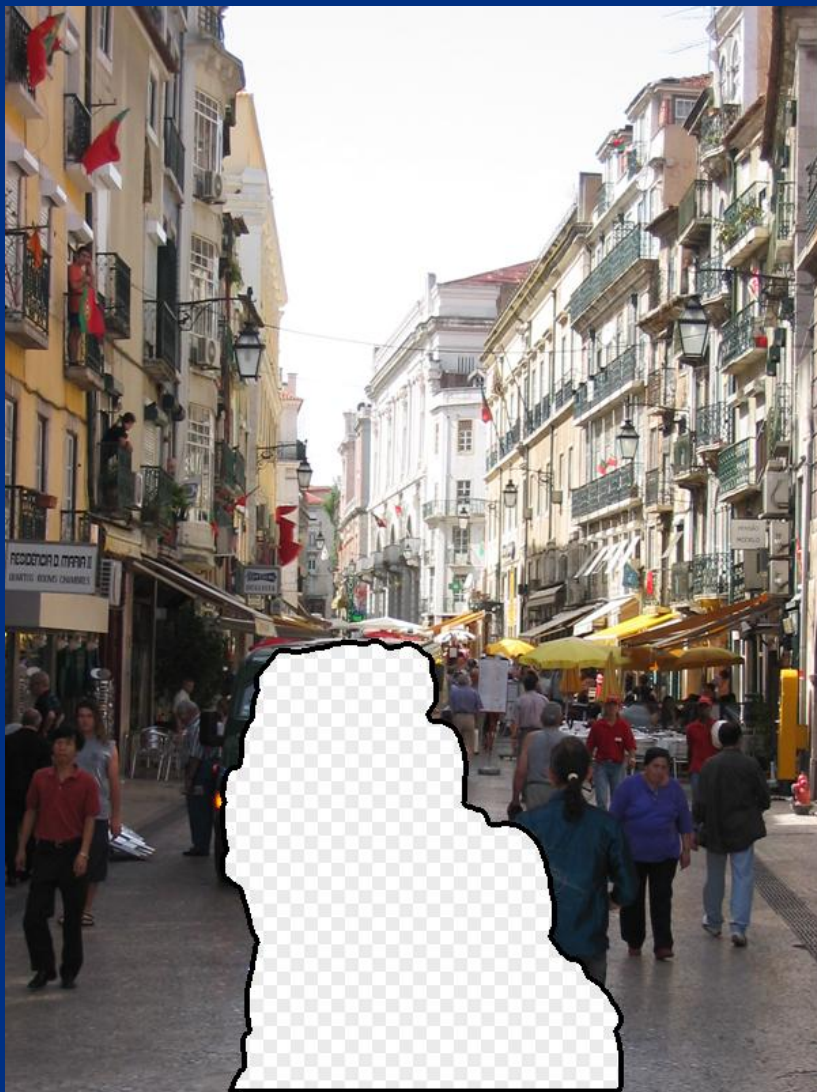




# Failures

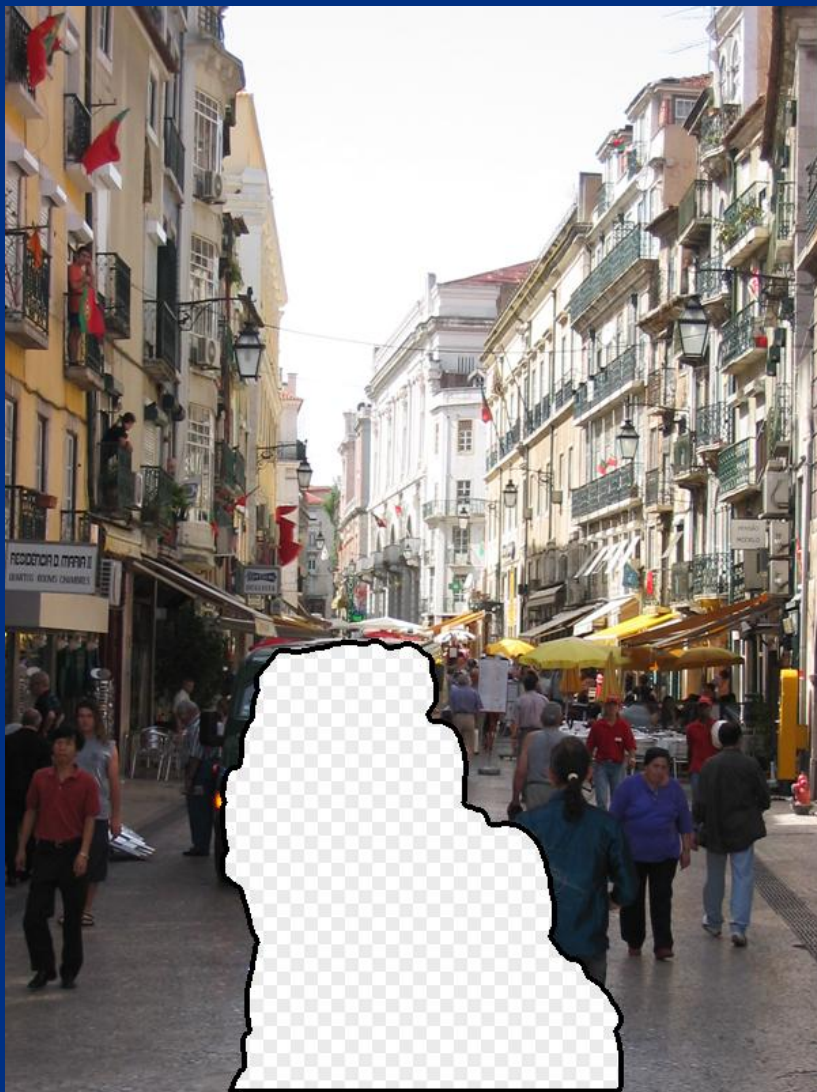


# Failures



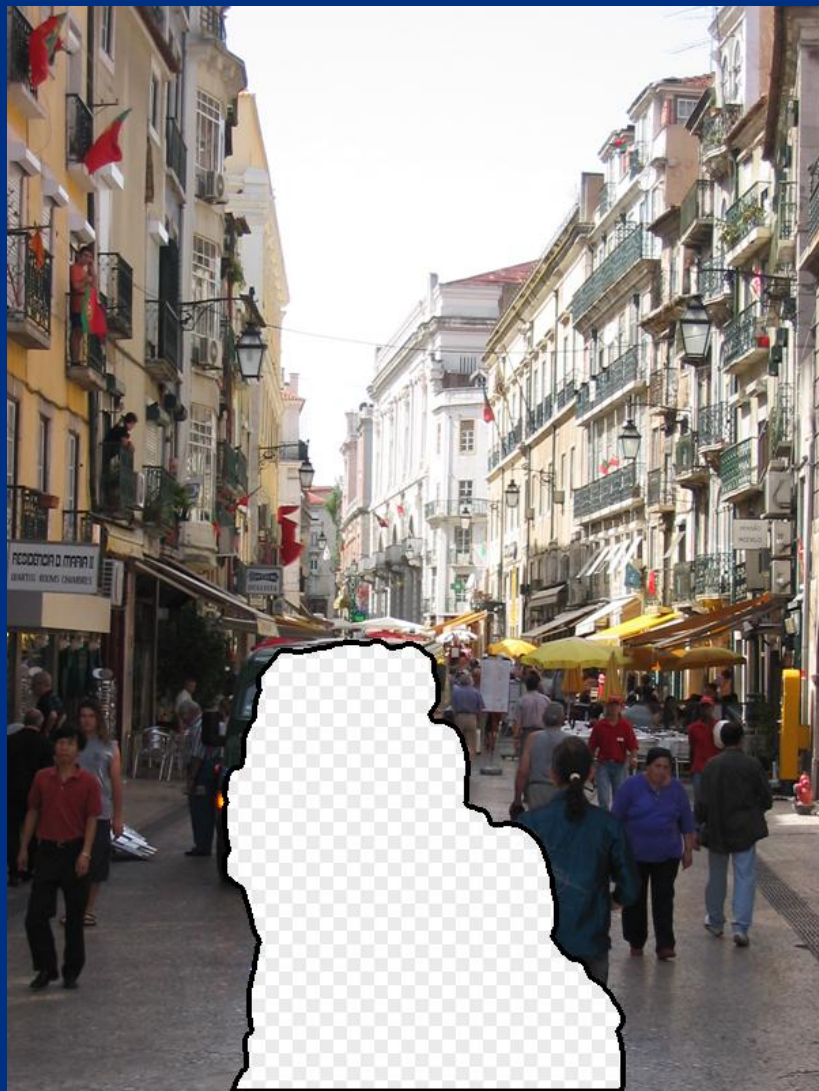


# Failures





# Failures



# Evaluation





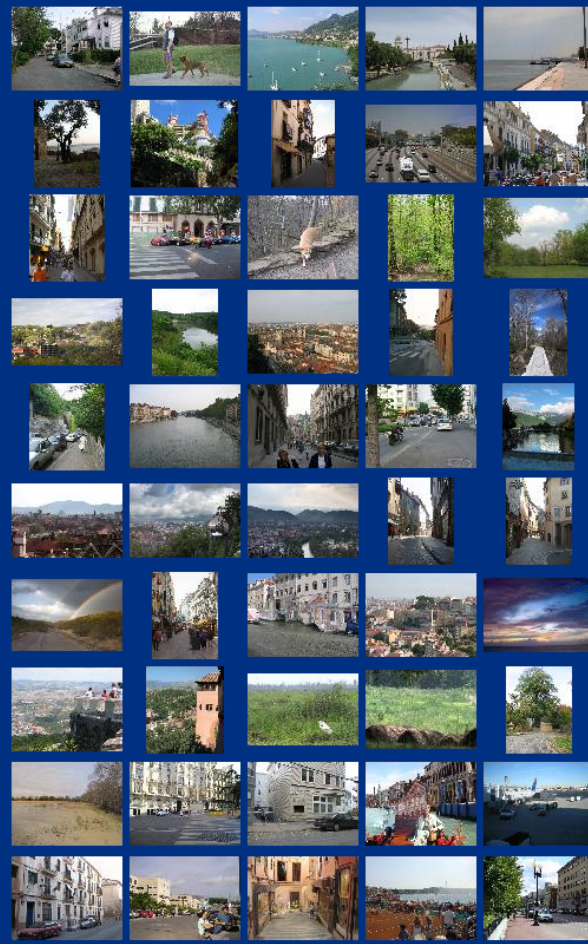


Original Images



Criminisi et al.

Single result



Scene Completion

Each result selected from 20



Original Images

Criminisi et al.

Scene Completion

Single result

Each result selected from 20





Real Image. This image has not  
been manipulated

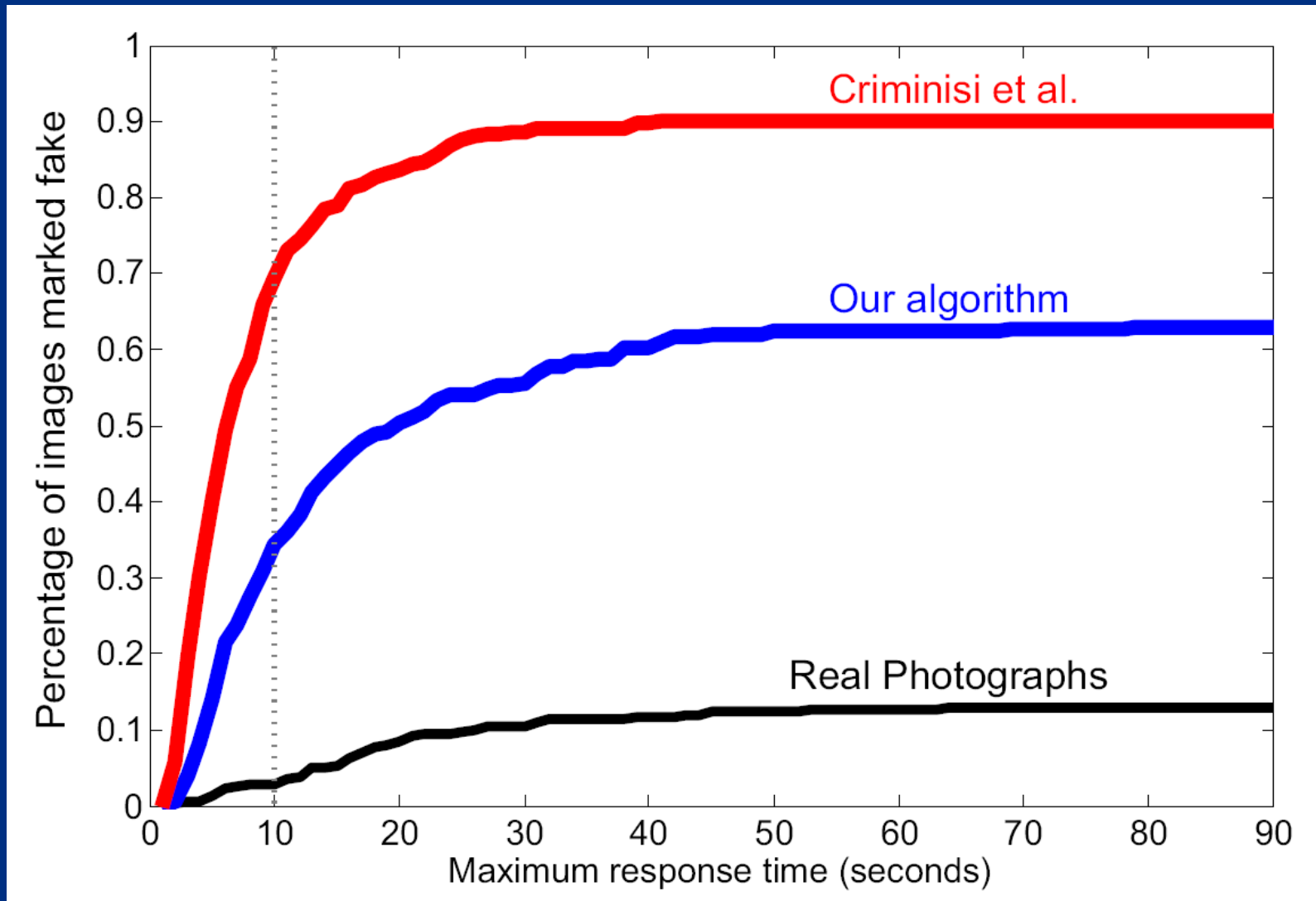
or

Fake Image. This image has been  
manipulated



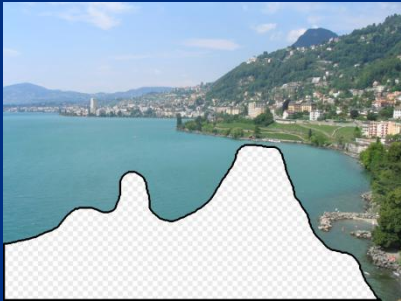


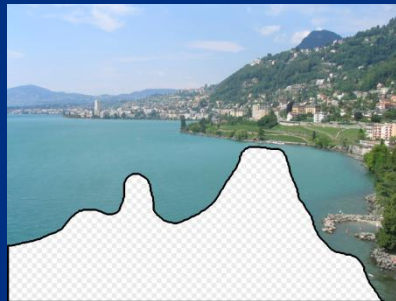
# User Study Results - 20 Participants





Why does it work?



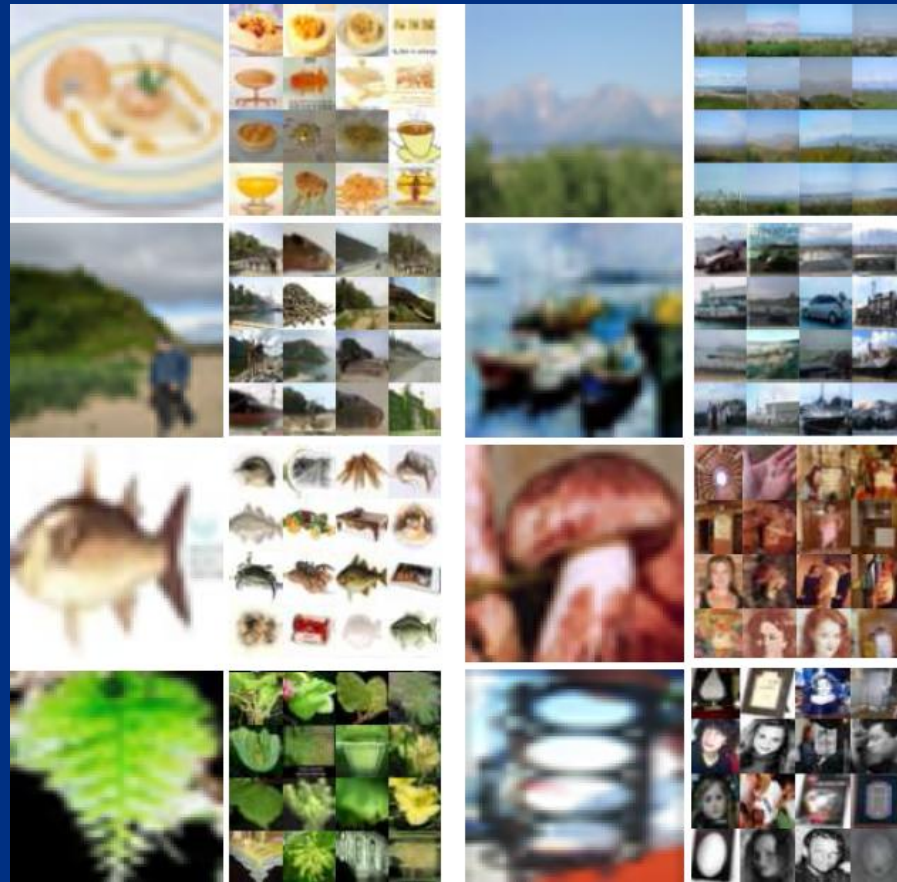


10 nearest neighbors from a collection of 20,000 images





10 nearest neighbors from a collection of 2 million images



Database of 70 Million 32x32 images

Torralba, Fergus, and Freeman. Tiny Images.  
MIT-CSAIL-TR-2007-024. 2007.

# The Small Picture

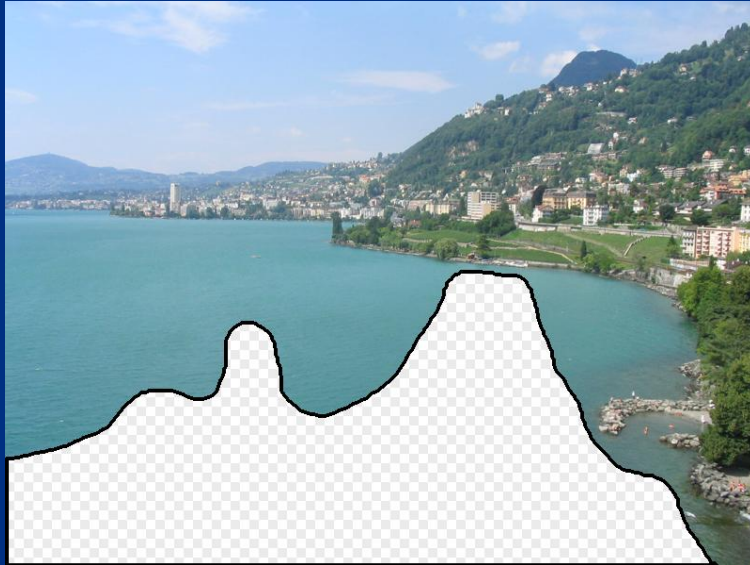


Image Collection



Pixels



Pixels + Semantics



# Hybrid Solution?

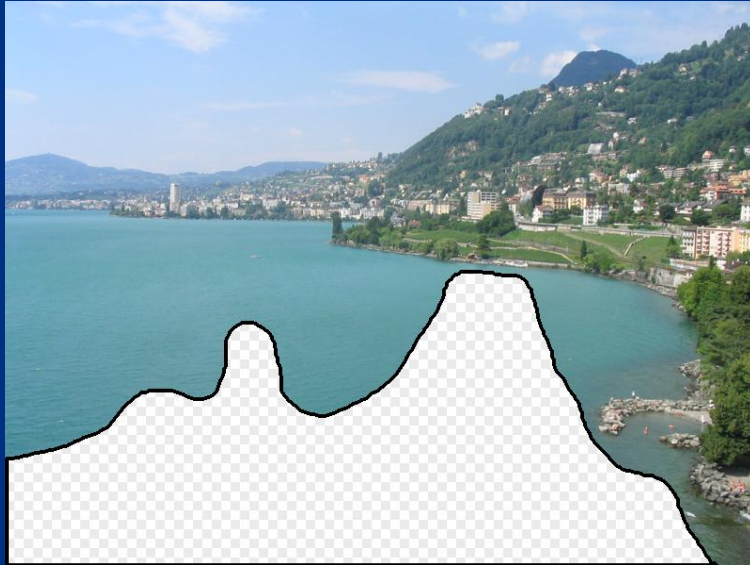


Image Collection



Pixels



Semantics

# The Big Picture



Sky, Water, Hills, Beach,  
Sunny, mid-day

Brute-force Image Understanding

# 80 Million Tiny Images



Massachusetts  
Institute of  
Technology

Antonio Torralba

Rob Fergus

William T. Freeman





# Admin

- HW4 due on Thursday 12<sup>th</sup> May
- This is a hard deadline!
- The TA has to grade the assignment by Saturday so I can turn in grades

# Overview

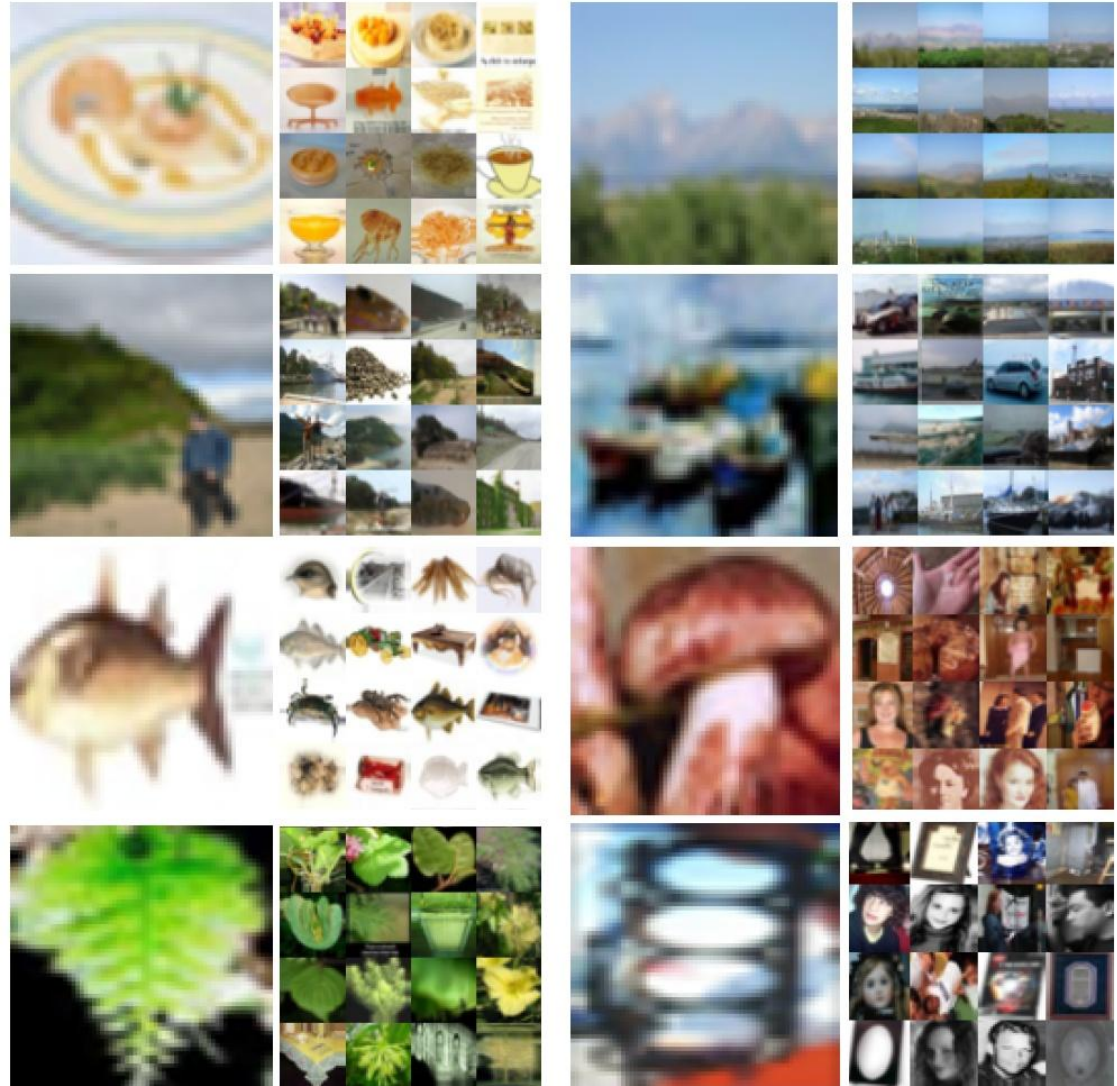
- Non-parametric approach to category-level recognition
- Dataset of 80 million images from Internet



- Use very low resolution images (32x32 color)

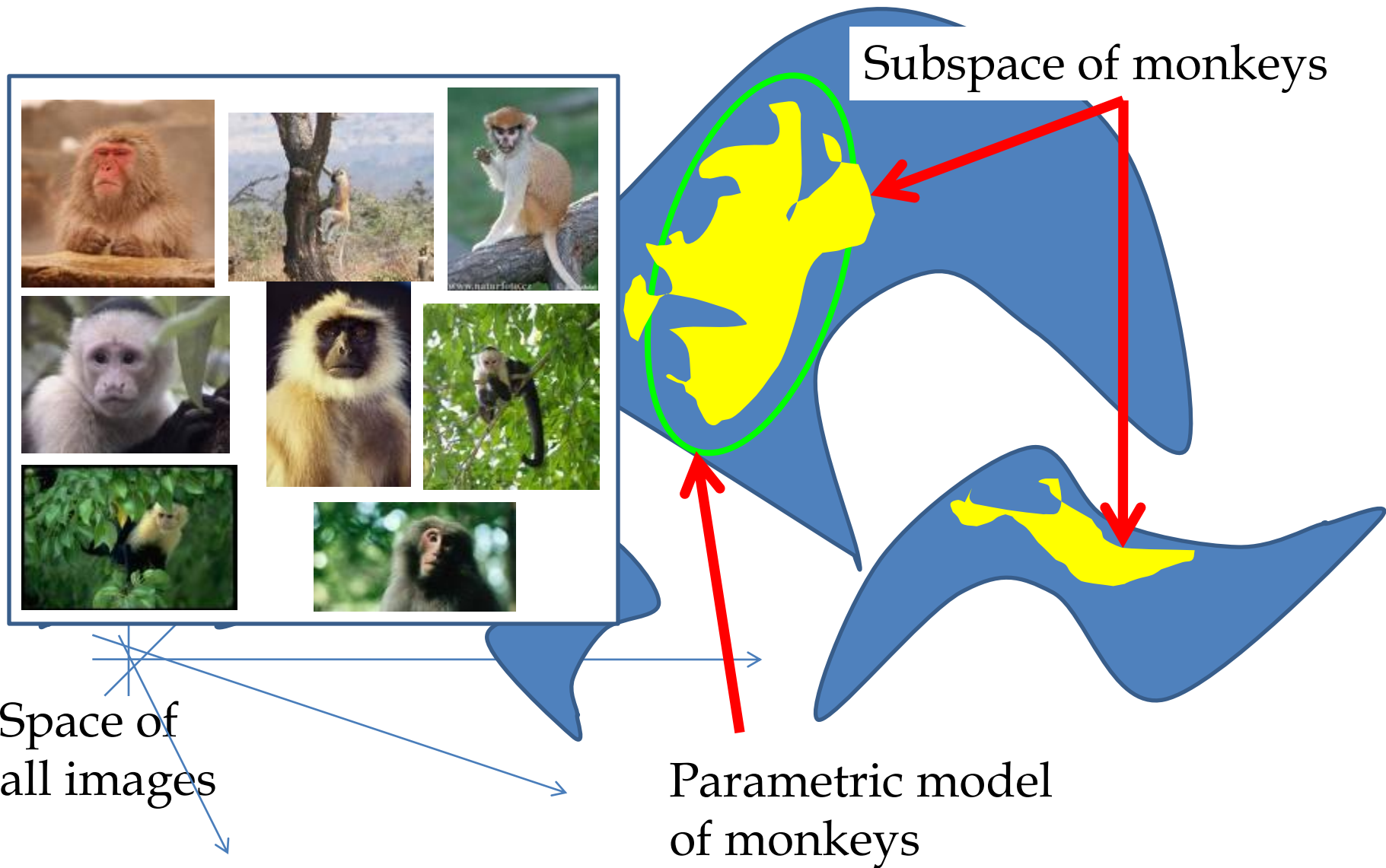
# Overview

- Use simple algorithms: nearest neighbors





# Motivation

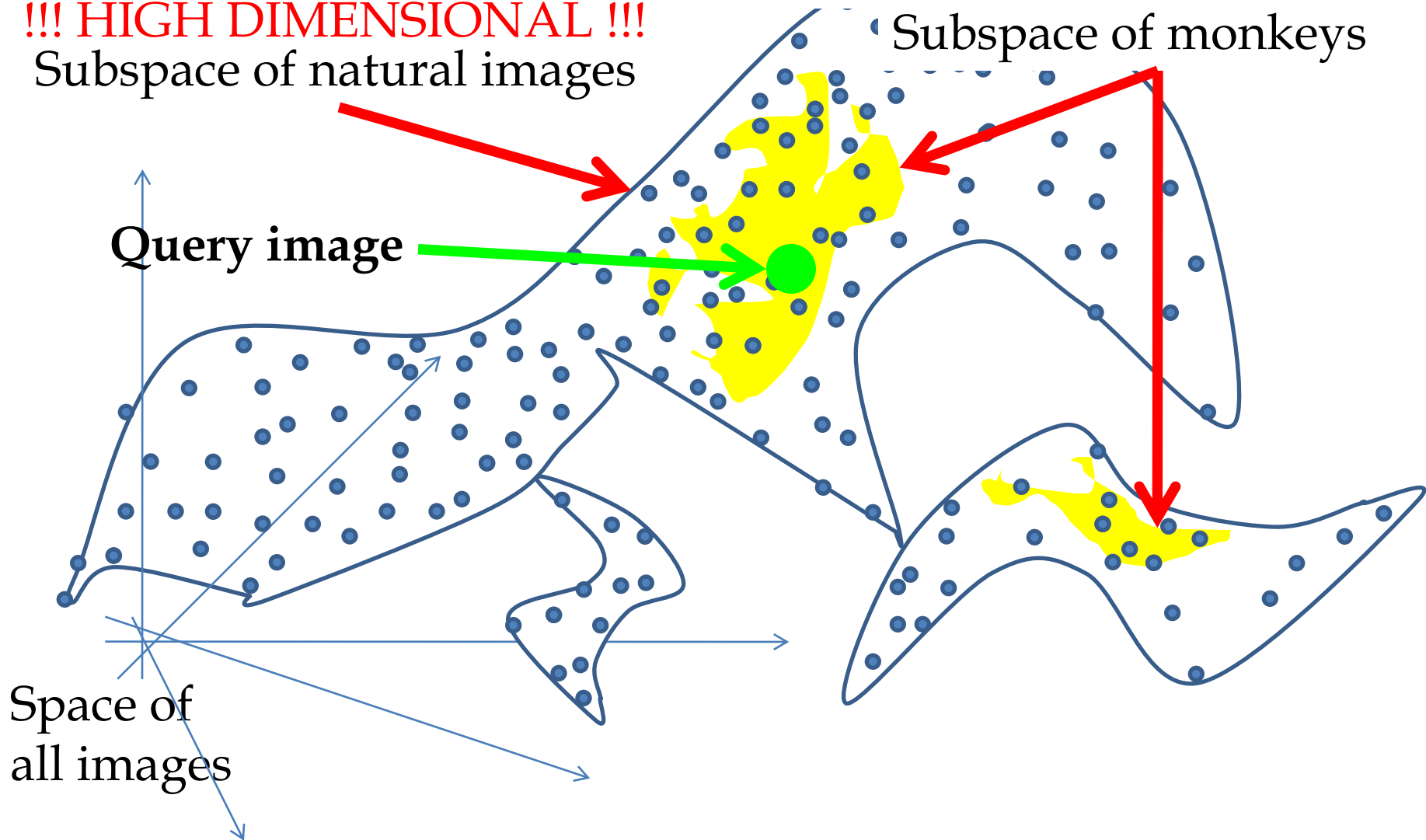


# Non-parametric Approach

!!! HIGH DIMENSIONAL !!!  
Subspace of natural images

!!! HIGH DIMENSIONAL !!!

Subspace of monkeys

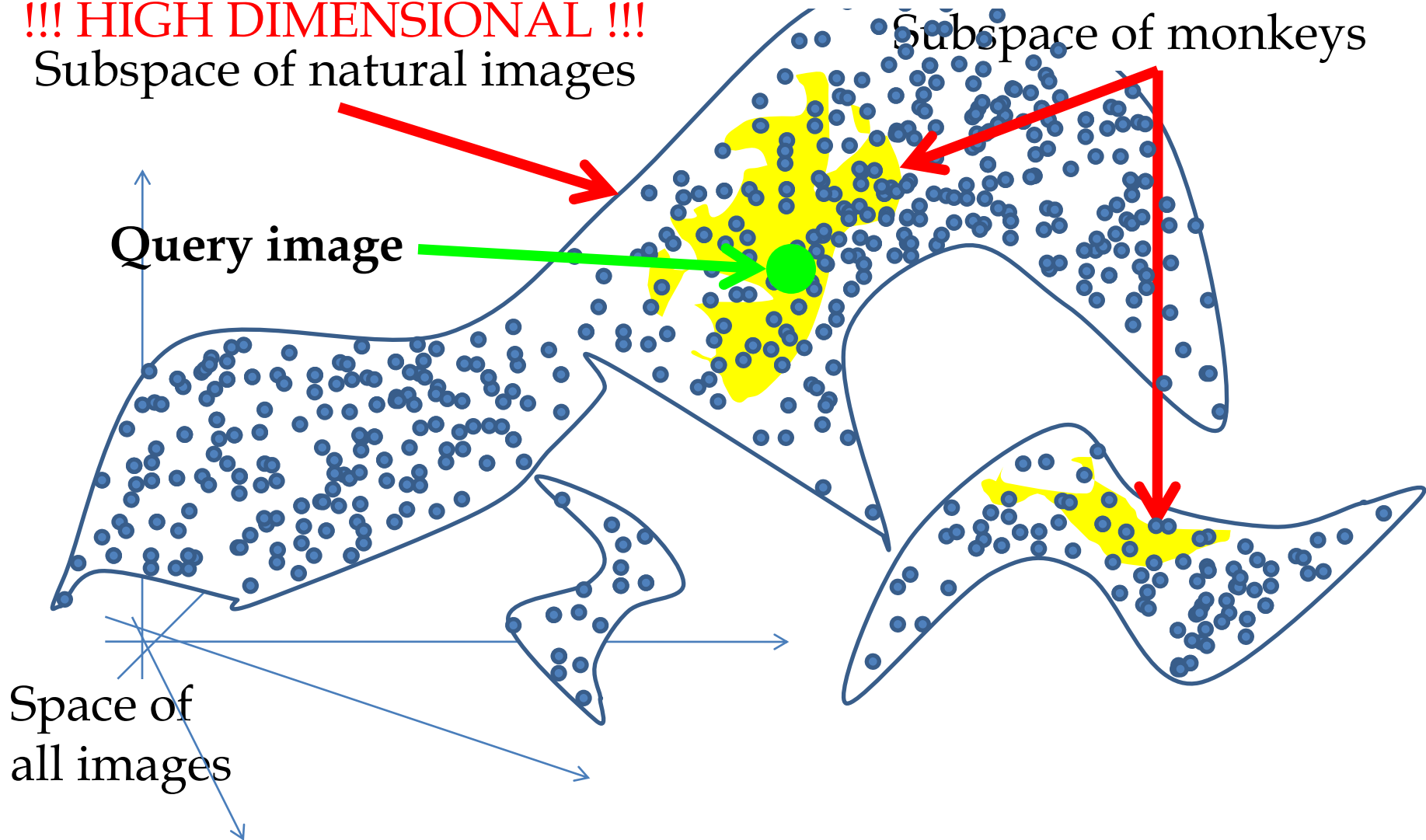


# Non-parametric Approach

!!! HIGH DIMENSIONAL !!!  
Subspace of natural images

!!! HIGH DIMENSIONAL !!!

Subspace of monkeys



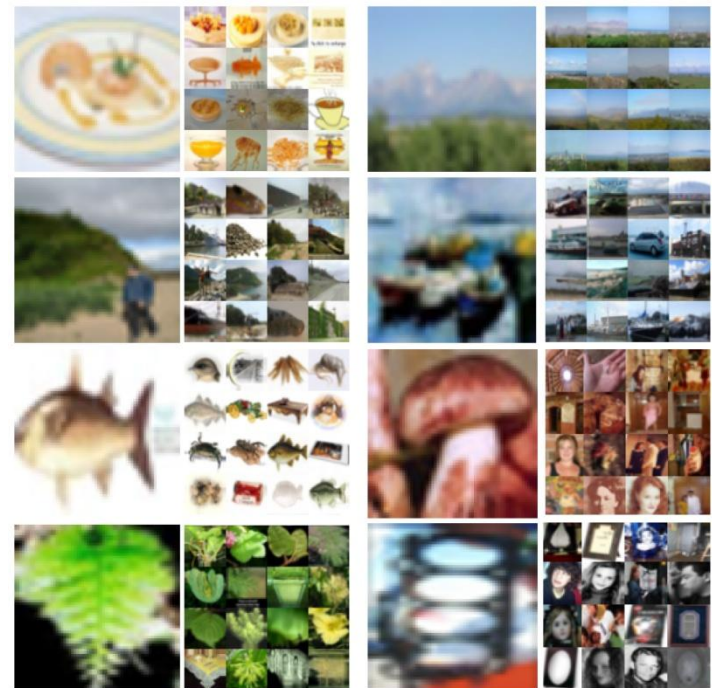


# Non-parametric Classifier

- Nearest-neighbors
- For each query, obtain **sibling set** (neighbors)

- 3 different types of distance metric

- Hand-designed, use whole image



# Metric 1 - $D_{ssd}$

- Sum of squared differences (SSD)

$$D_{ssd}^2 = \sum_{x,y,c} \left[ \text{Image 1} - \text{Image 2} \right]^2$$

To give invariance to illumination:  
Each image normalized to  
be zero mean, unit variance



Target

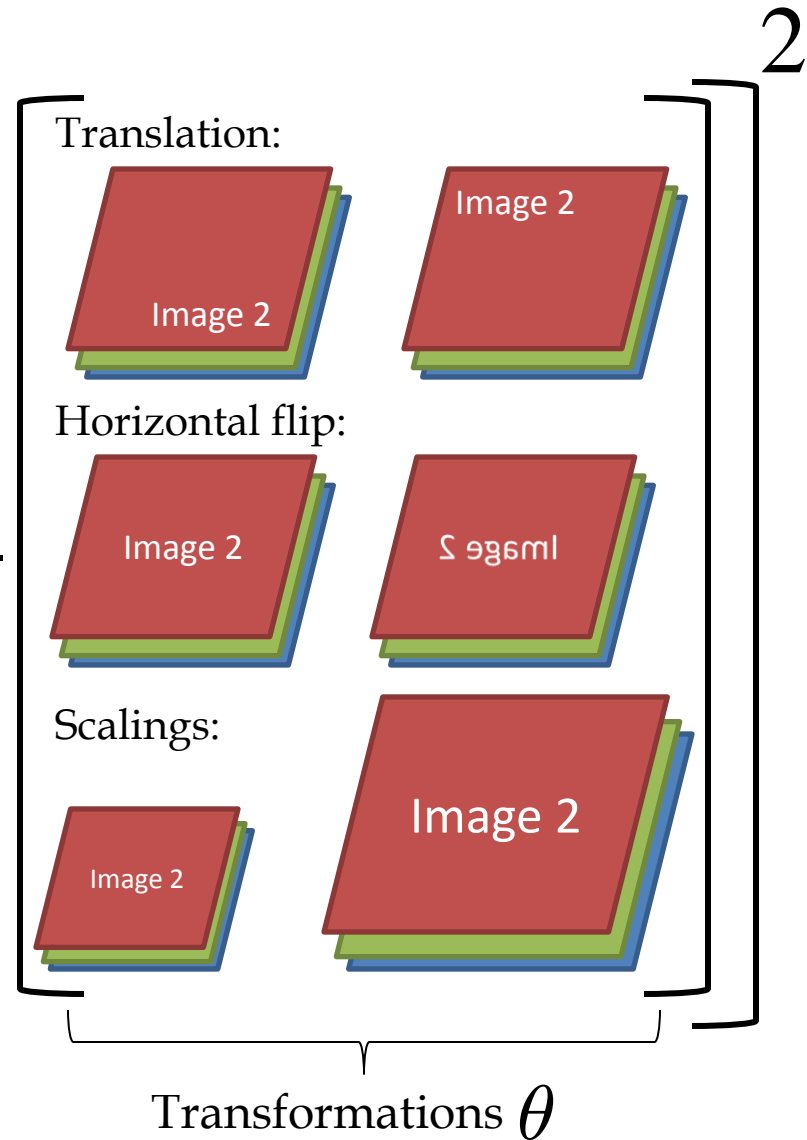
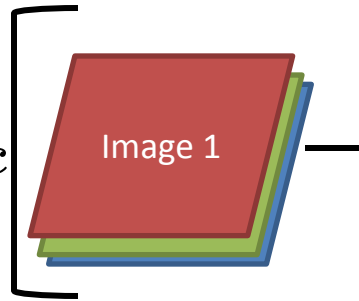


Neighbor

# Metric 2 - $D_{warp}$

- SSD but allow small transformations

$$D_{warp}^2 = \min_{\theta} \sum_{x,y,c}$$



Find min using gradient descent





# Metric 3 - $D_{shift}$

- As per Warping but also allow sub-window shifts

$$D_{shift}^2 = \sum_{x,y,c} \left[ \text{Image 1} - \underset{\theta}{\text{Transformed}} \left[ \text{Image 2} \right] \right]^2$$

Start with warped version of image 2, as per  $D_{warp}$

# Metric 3 - $D_{shift}$

- As per Warping but also allow sub-window shifts

$$D_{shift}^2 = \sum_{x,y,c} \left[ \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} - \text{Transformed } \theta \left[ \begin{array}{c} \text{Image 2} \\ \text{Image 2} \end{array} \right] \right]^2$$

The equation shows the squared difference between two images, where the second image is transformed by a parameter  $\theta$ . The images are represented by small car icons.

Start with warped version of image 2, as per  $D_{warp}$

# Metric 3 - $D_{shift}$

- As per Warping but also allow sub-window shifts

$$D_{shift}^2 = \sum_{x,y,c} \left[ \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} \right]^2$$

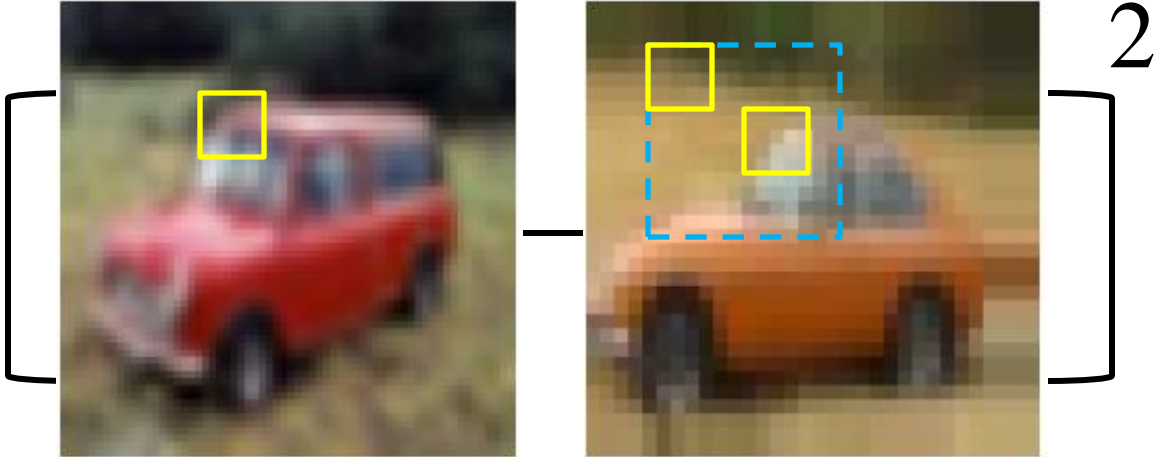
The equation shows the squared distance metric  $D_{shift}^2$  as a sum over pixels  $(x, y, c)$  of the squared difference between two images. The first image is a red car, and the second image is an orange car. The images are shown as small square patches within the equation's structure.

Start with warped version of image 2, as per  $D_{warp}$



# Metric 3 - $D_{shift}$

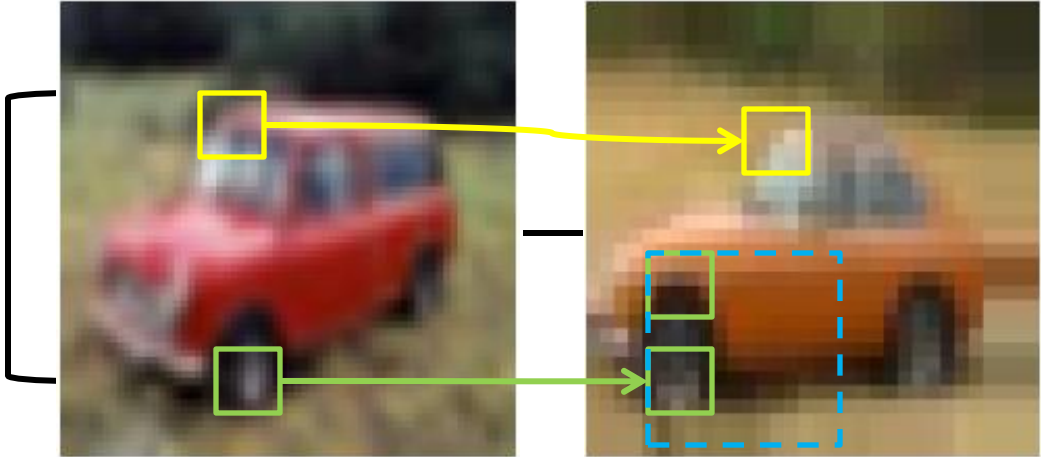
- As per Warping but also allow sub-window shifts

$$D_{shift}^2 = \min_{\text{Local sub-window}} \sum_{x,y,c}$$


The diagram illustrates the  $D_{shift}$  metric. It shows two images of a car. The left image is a red car with a yellow bounding box. The right image is an orange car with a yellow bounding box and a blue dashed bounding box. A large bracket on the right side of the images is labeled with the number 2.

# Metric 3 - $D_{shift}$

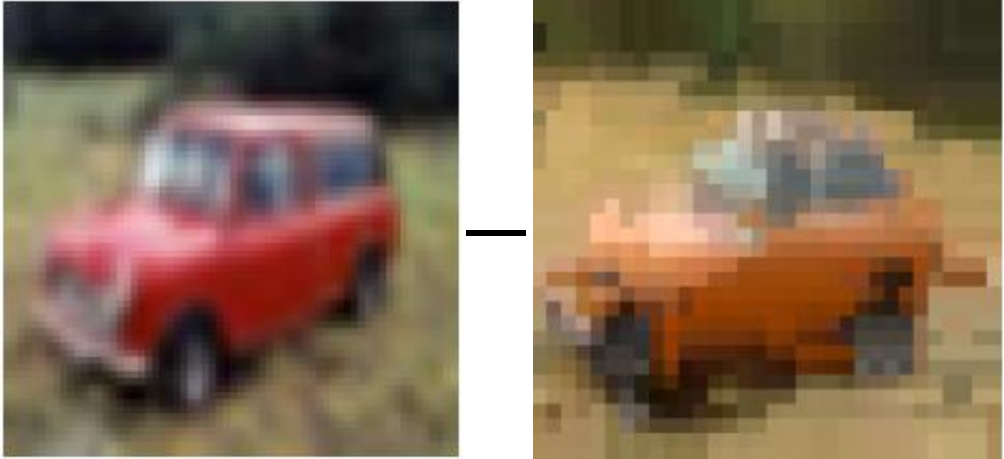
- As per Warping but also allow sub-window shifts

$$D_{shift}^2 = \min_{\text{Local sub-window}} \sum_{x,y,c}$$


- Quick since images are so small

# Metric 3 - $D_{shift}$

- As per Warping but also allow sub-window shifts

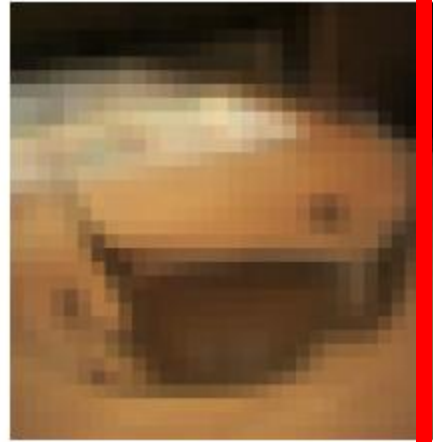
$$D_{shift}^2 = \min_{\text{Local sub-window}} \sum_{x,y,c} \left[ \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} \right]^2$$


Tried various sizes of sub-window

→ 1x1 (i.e. single pixel) worked best



# Comparison of metrics



Target

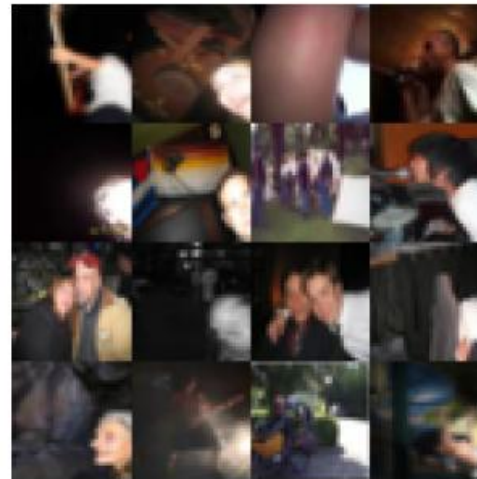
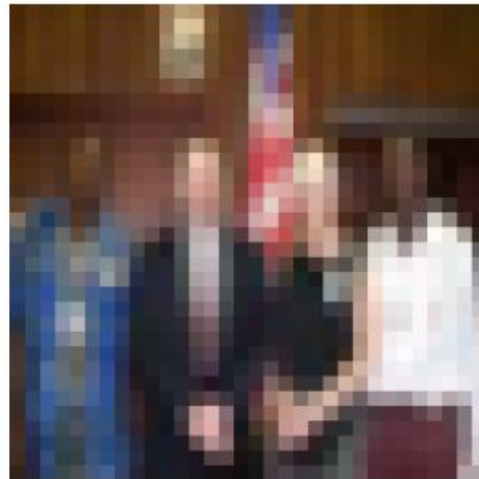
SSD

Warping

Pixel shifting

# Sibling Sets with Different Metrics

- Sibling set is 50 images

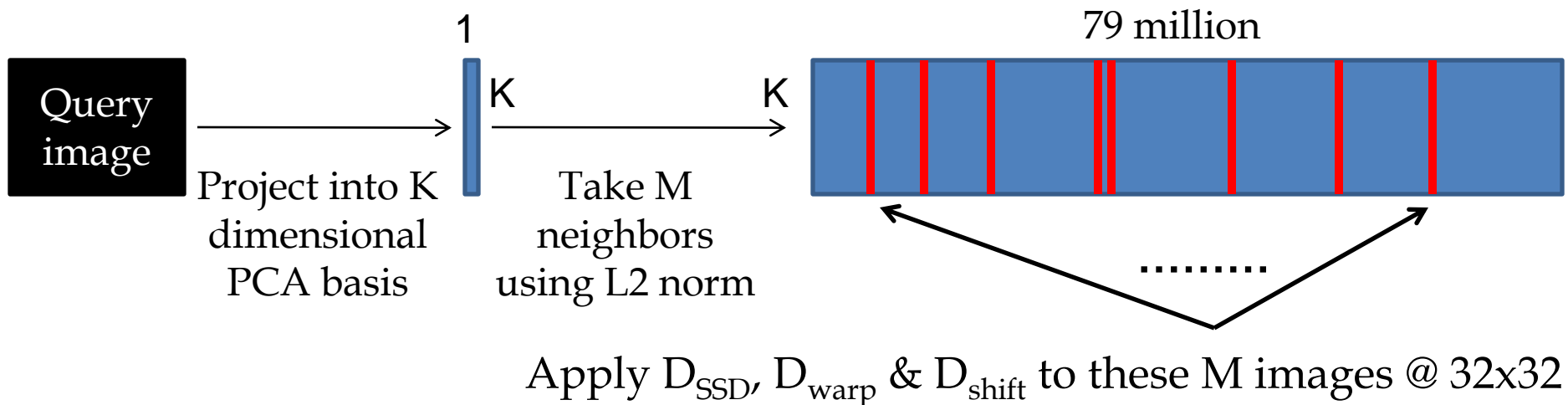


$D_{ssd}$

$D_{shift}$

# Approximate $D_{SSD}$

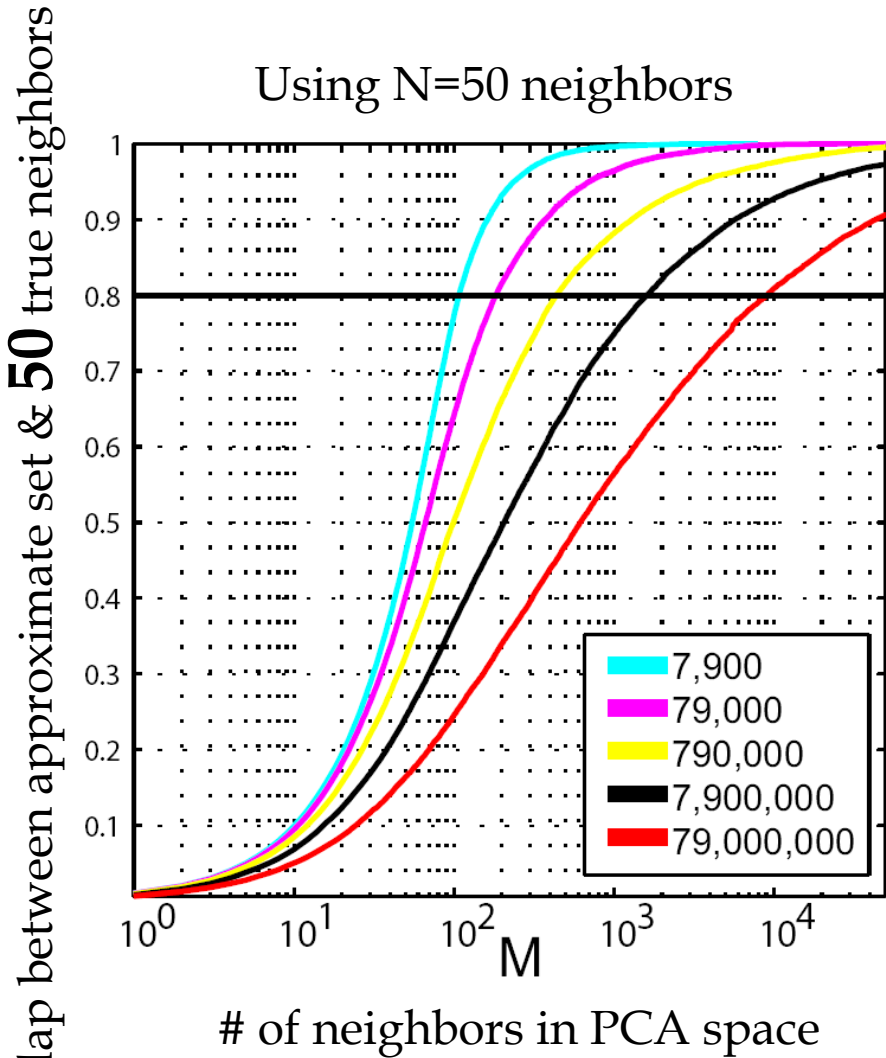
- Exact distance metrics are too expensive to apply to all 79 million images
- Use approximate scheme based on taking first  $K=19$  principal components



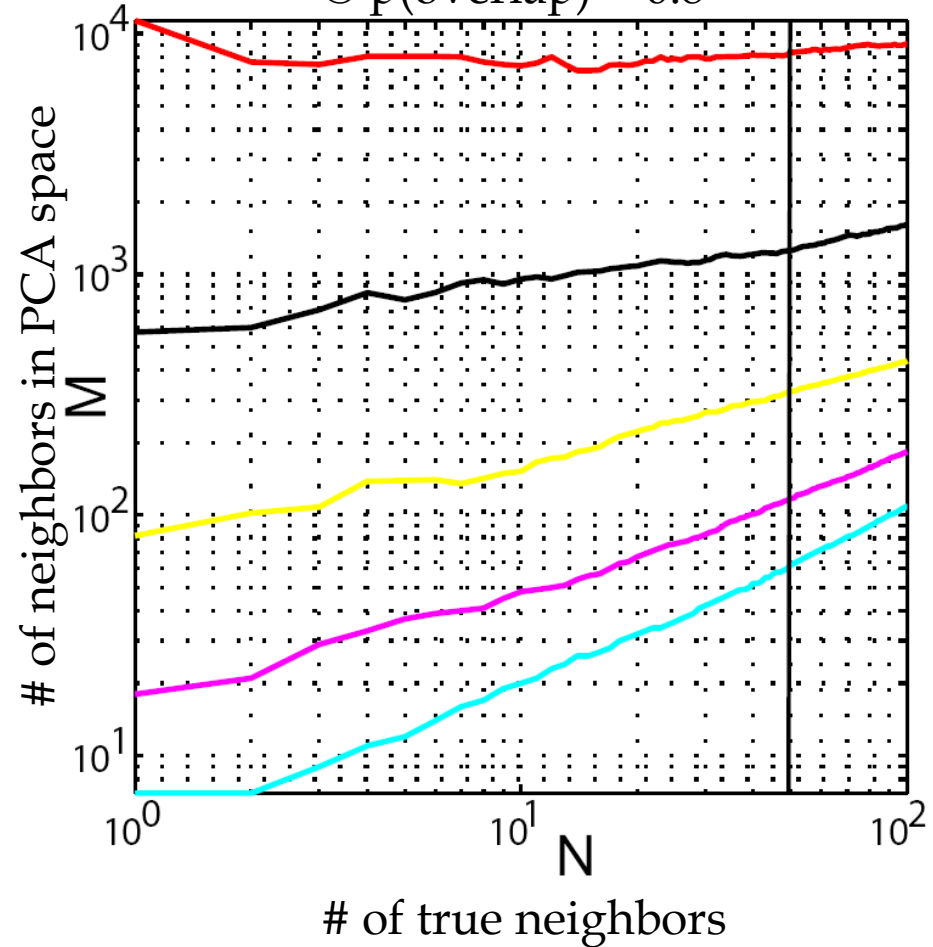


# Exact SSD vs Approximate SSD

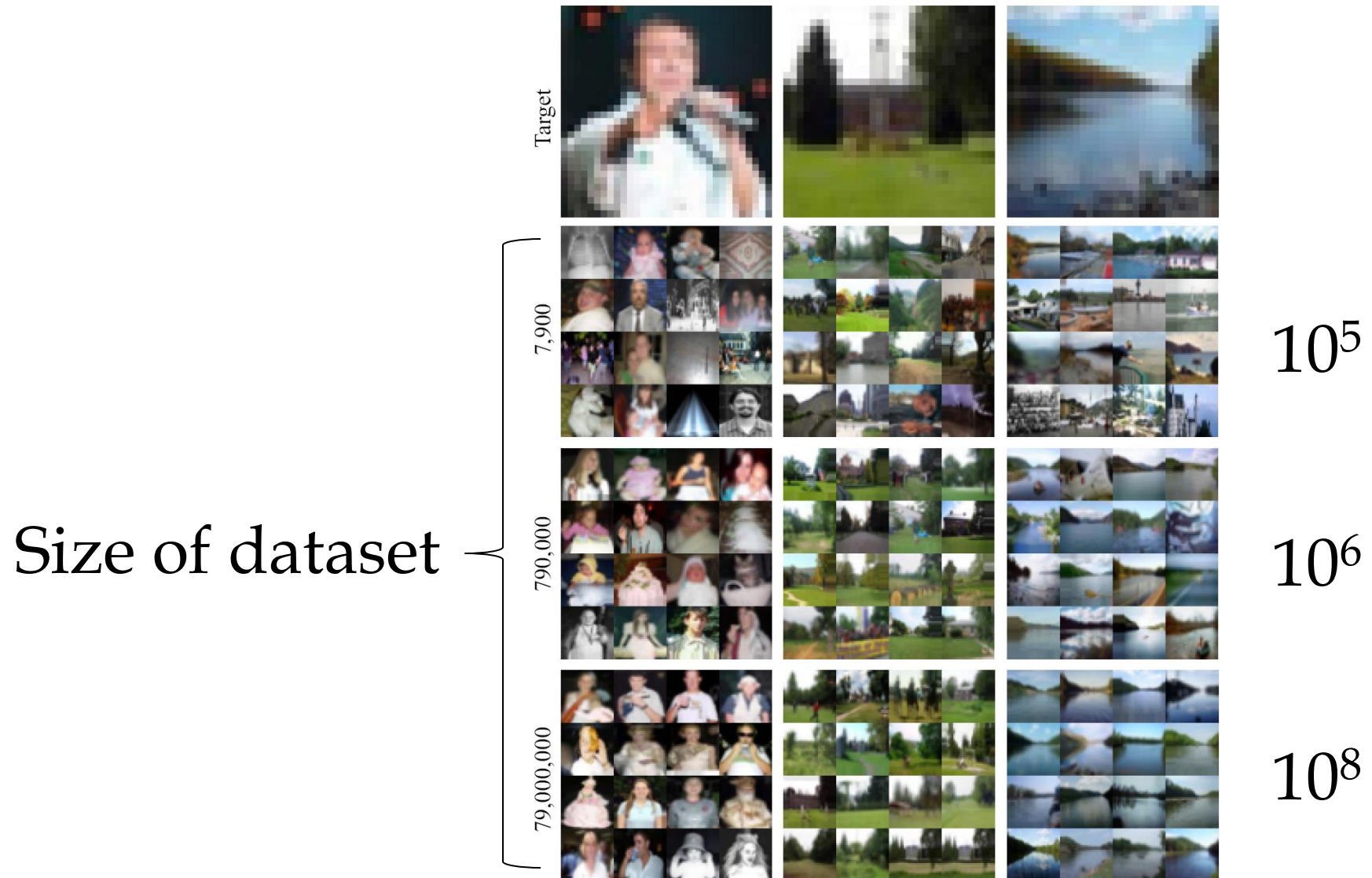
Using  $N=50$  neighbors



@  $p(\text{overlap}) = 0.8$



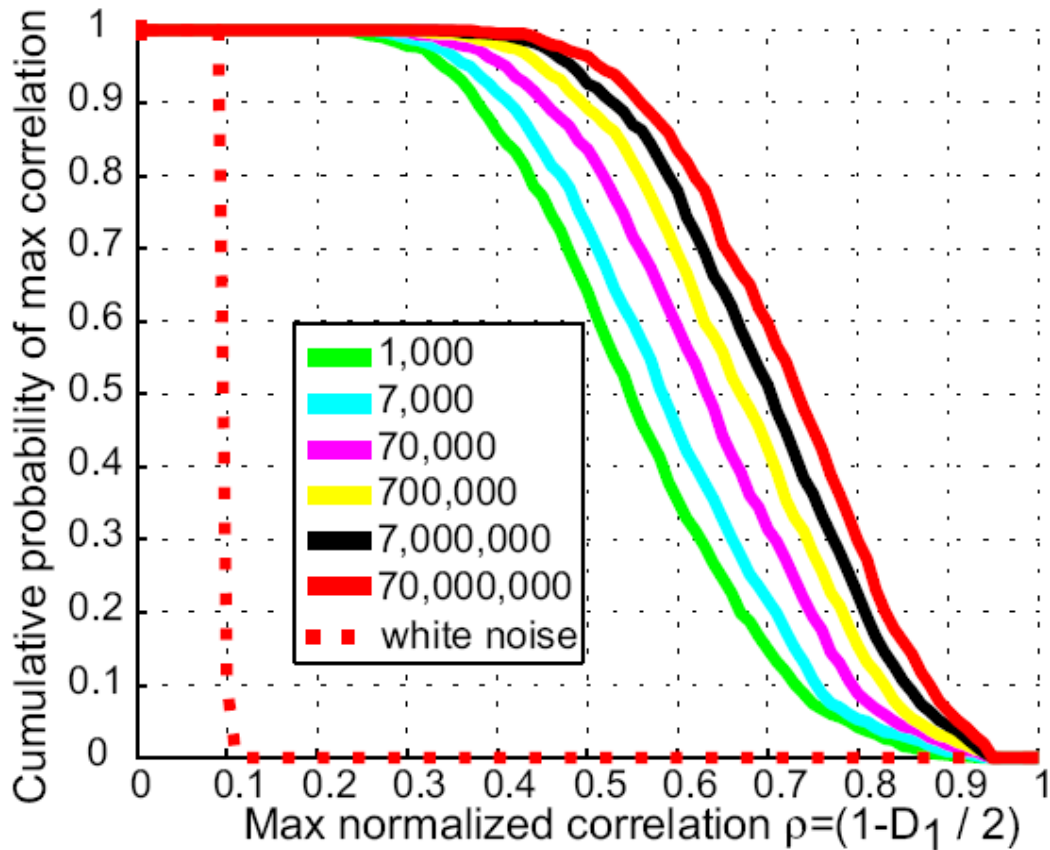
# Quality of Sibling Set using $D_{\text{shift}}$



# **Exploring the Sub-Space of Natural Images**



# How Many Images Are There?



Note:  $D_1 = D_{SSD}$

# Examples

Normalized correlation scores:

skagerak

(0.94)

(0.74)

(0.74)

(0.72)

(0.70)

(0.65)

(0.60)

(0.50)



katmandu

(0.93)

(0.92)

(0.91)

(0.90)

(0.85)

(0.80)

(0.75)

(0.70)



noether

(0.93)

(0.92)

(0.91)

(0.90)

(0.85)

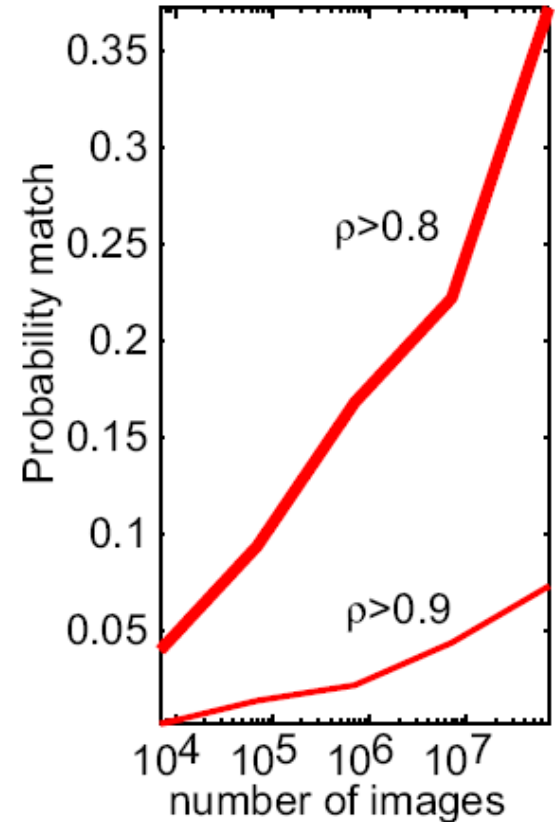
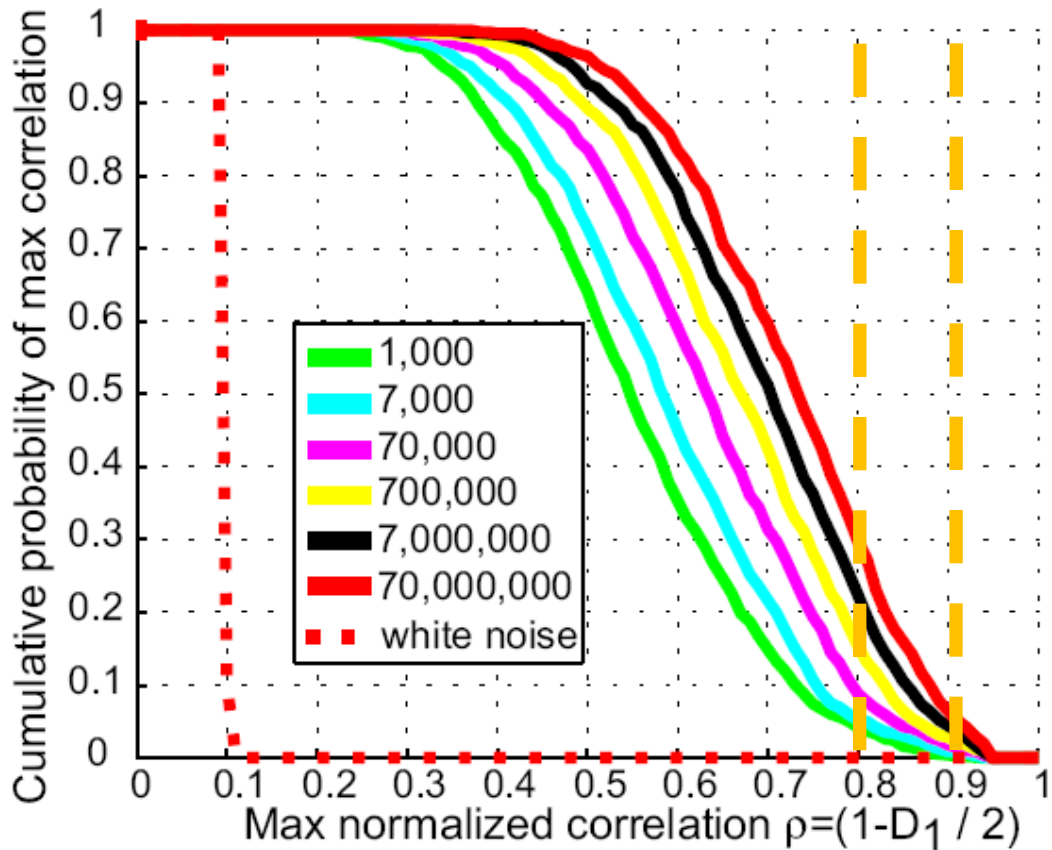
(0.80)

(0.75)

(0.70)



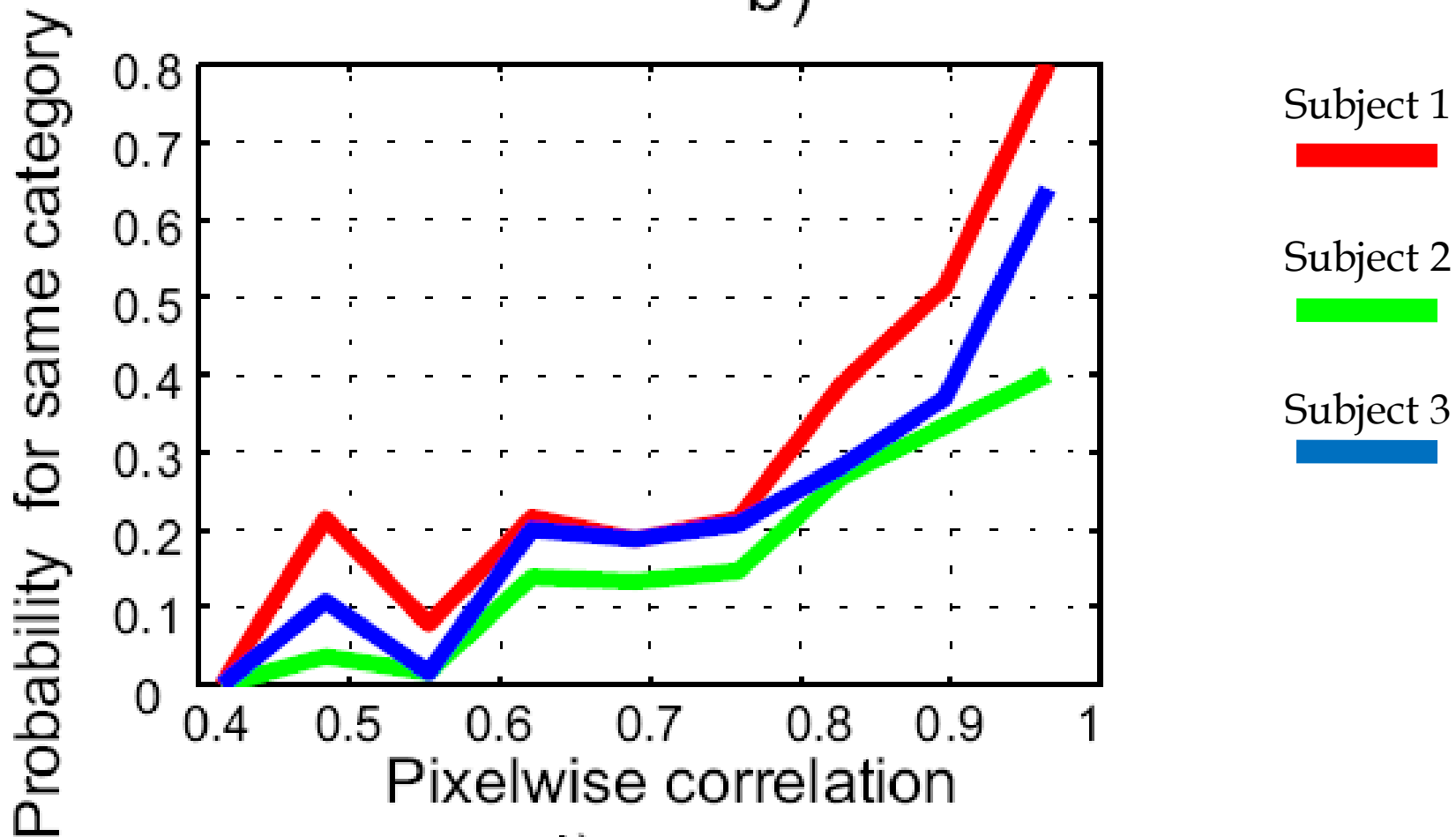
# How Many Images Are There?



Note:  $D_1 = D_{SSD}$

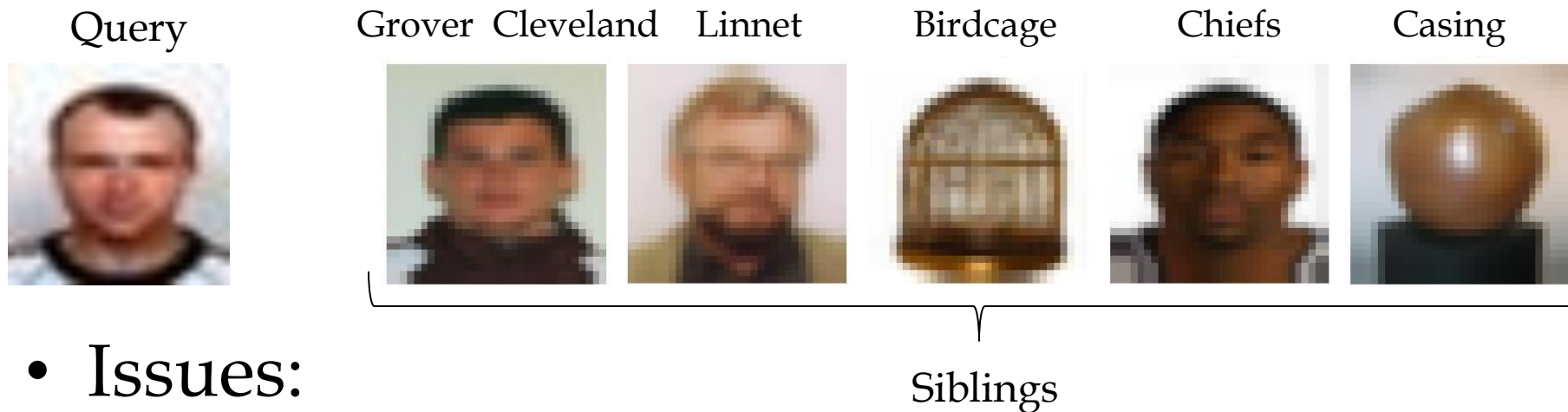


# How Does $D_{ssd}$ Relate to Semantic Distance?



# Label Assignment

- Distance metrics give set of nearby images
- How to compute label?



- Issues:
  - Labeling noise
  - Keywords can be very specific
    - e.g. yellowfin tuna

# Wordnet – a Lexical Dictionary

<http://wordnet.princeton.edu/>

Synonyms/Hypernyms (Ordered by Estimated Frequency) of noun **aardvark**

Sense 1

**aardvark**, ant bear, anteater, *Orycteropus afer*

=> placental, placental mammal, eutherian, eutherian mammal

=> mammal

=> vertebrate, craniate

=> chordate

=> animal, animate being, beast, brute, creature

=> organism, being

=> living thing, animate thing

=> object, physical object

=> entity



# Wordnet Hierarchy

Synonyms/Hypernyms (Ordered by Estimated Frequency) of noun **ardvark**

## Sense 1

**ardvark**, ant bear, anteater, Orycteropus afer

=> **placental**, placental mammal, eutherian, eutherian mammal

=> **mammal**

=> **vertebrate**, craniate

=> **chordate**

=> **animal**, animate being, beast, brute, creature

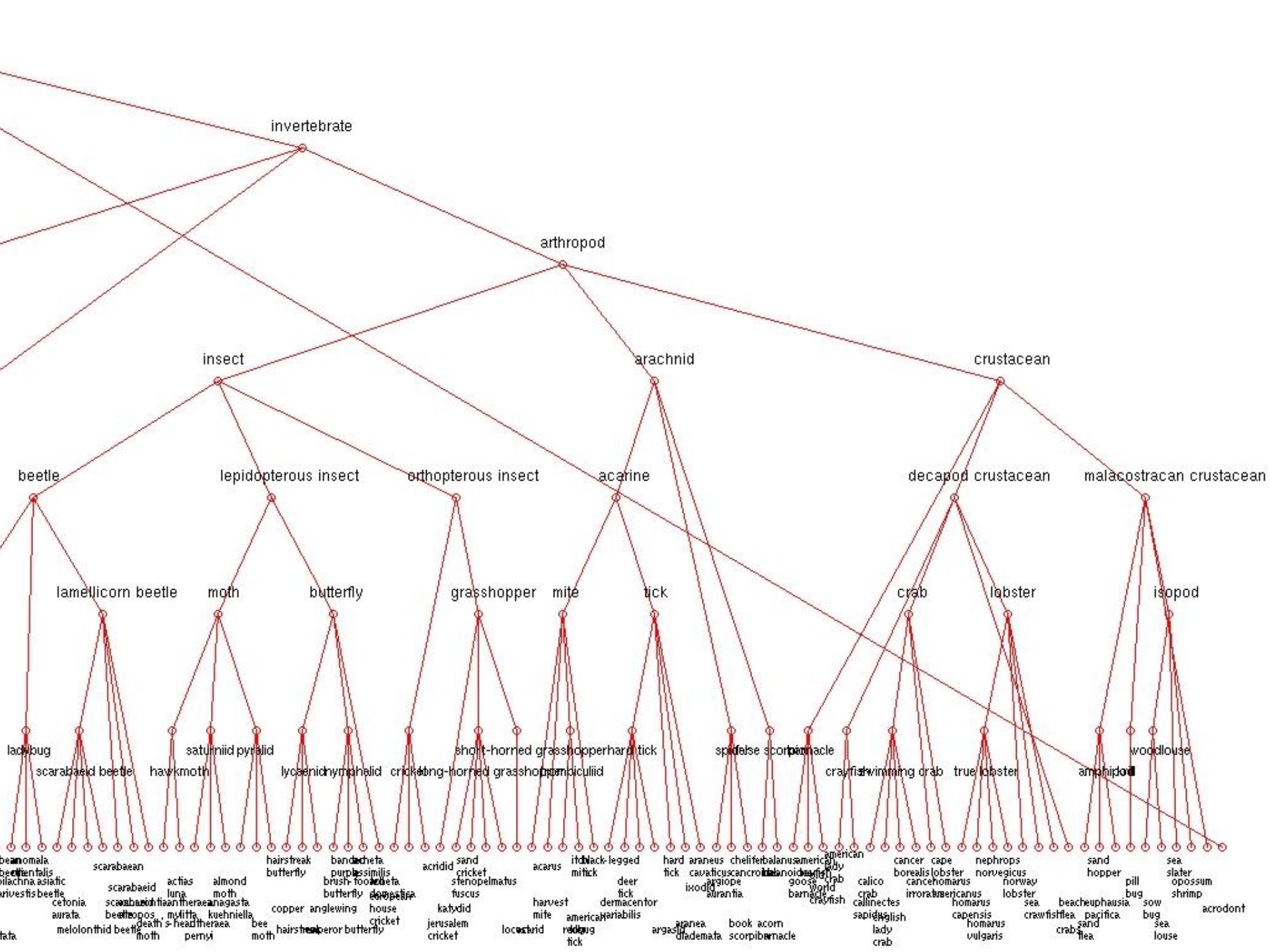
=> **organism**, being

=> **living thing**, animate thing

=> **object**, physical object

=> **entity**

- Convert graph structure into tree by taking most common meaning



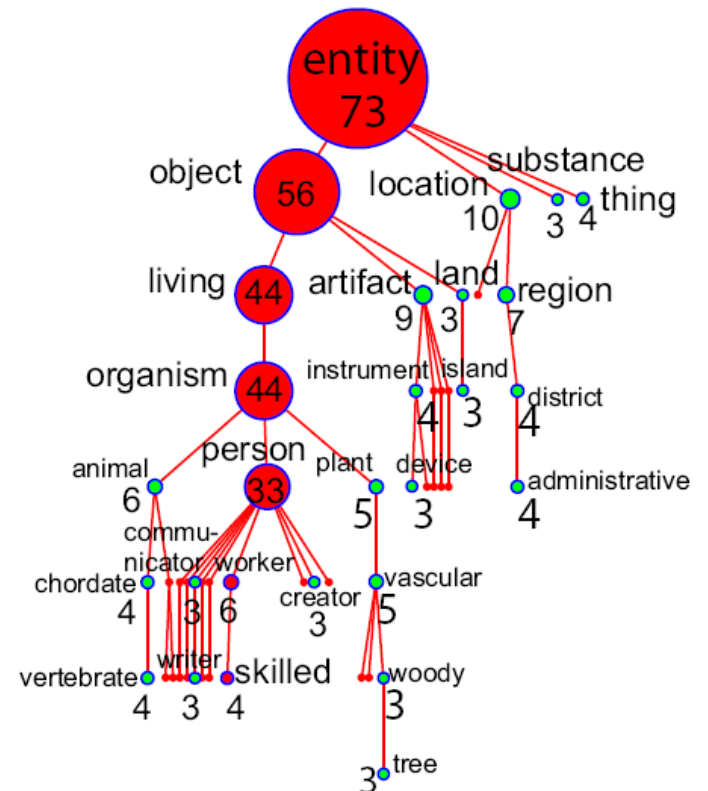
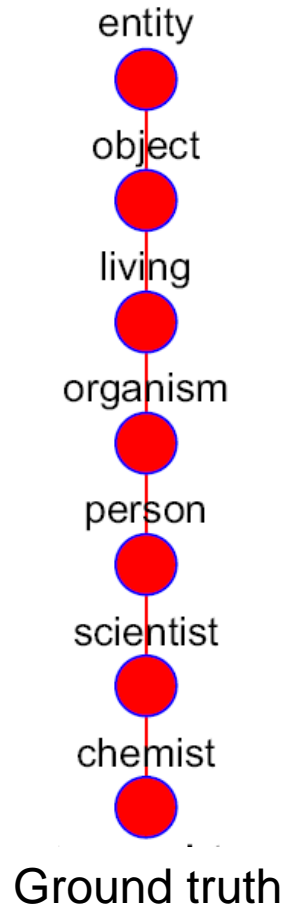
# Wordnet Voting Scheme



a) Input image



b) Neighbors

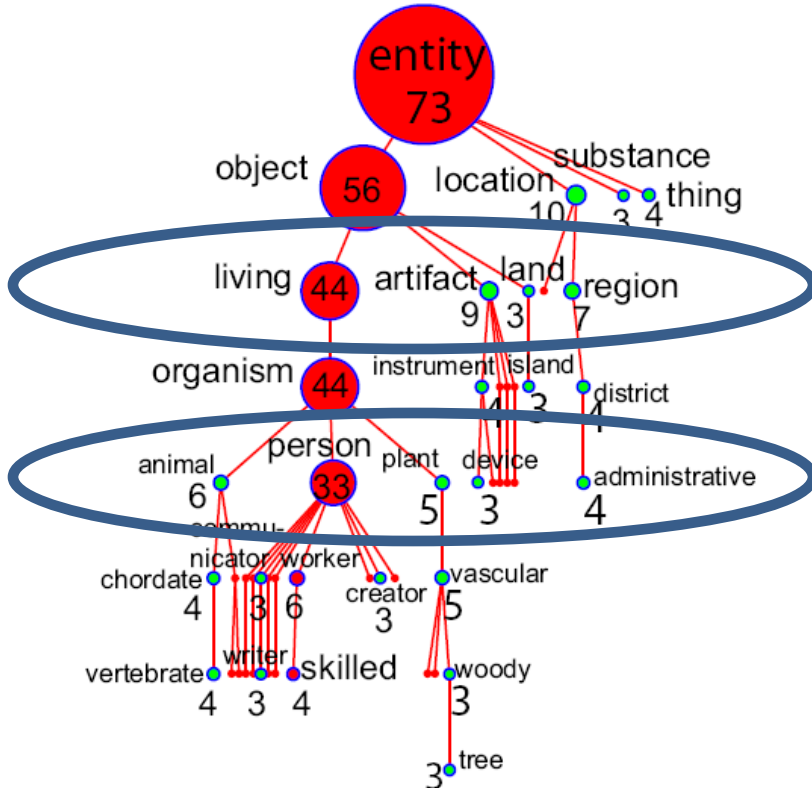


d) Wordnet voted branches

**One image - one vote**



# Classification at Multiple Semantic Levels



Votes:

Living	44
Artifact	9
Plant	5
Region	7
Administrative	4
Others	22

1 d) Wordnet voted branches

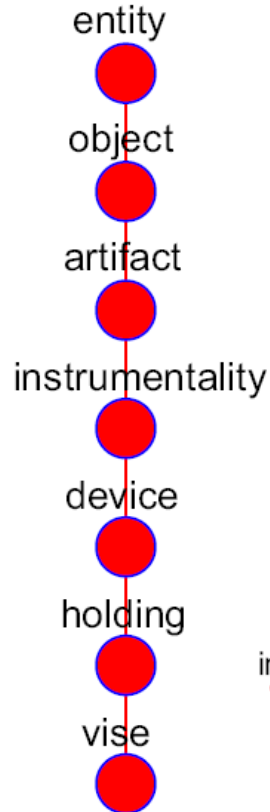
# Wordnet Voting Scheme



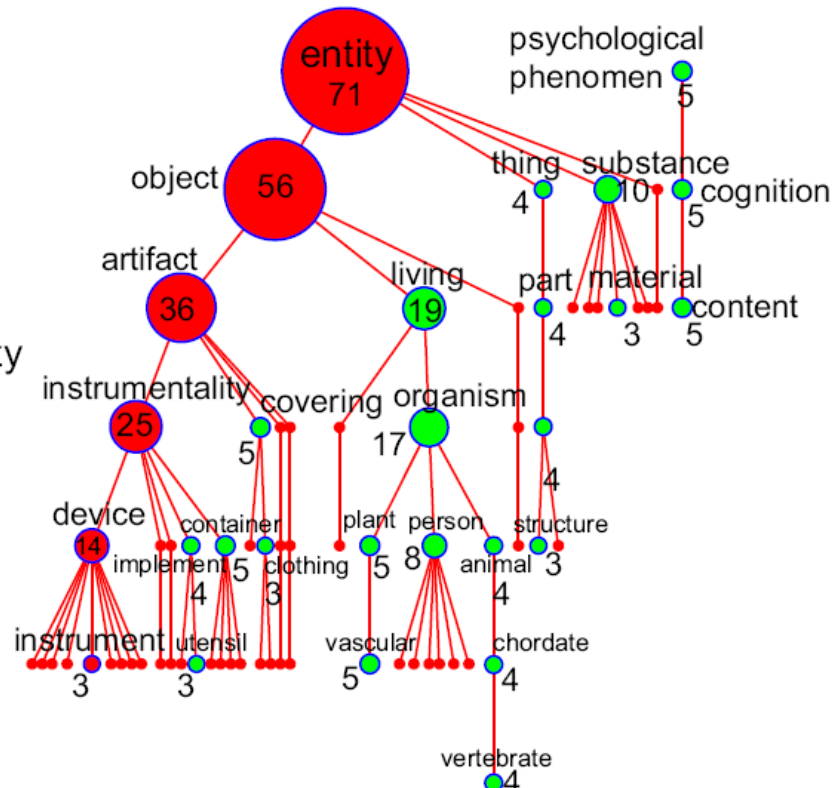
a) Input image



b) Neighbors



c) Ground truth



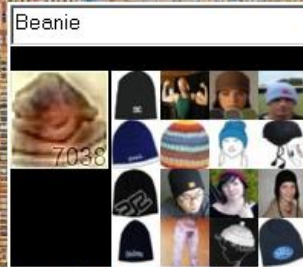
d) Wordnet voted branches

# Wordnet Voting

- Overcomes differences in level of semantic labeling:
  - e.g. “person” & “sir arthur conan doyle”
- Totally incorrect labels form hopefully uniform background noise
- Assumes semantic and visual consistency are closely related



# Semantic vs Visual Hierarchy

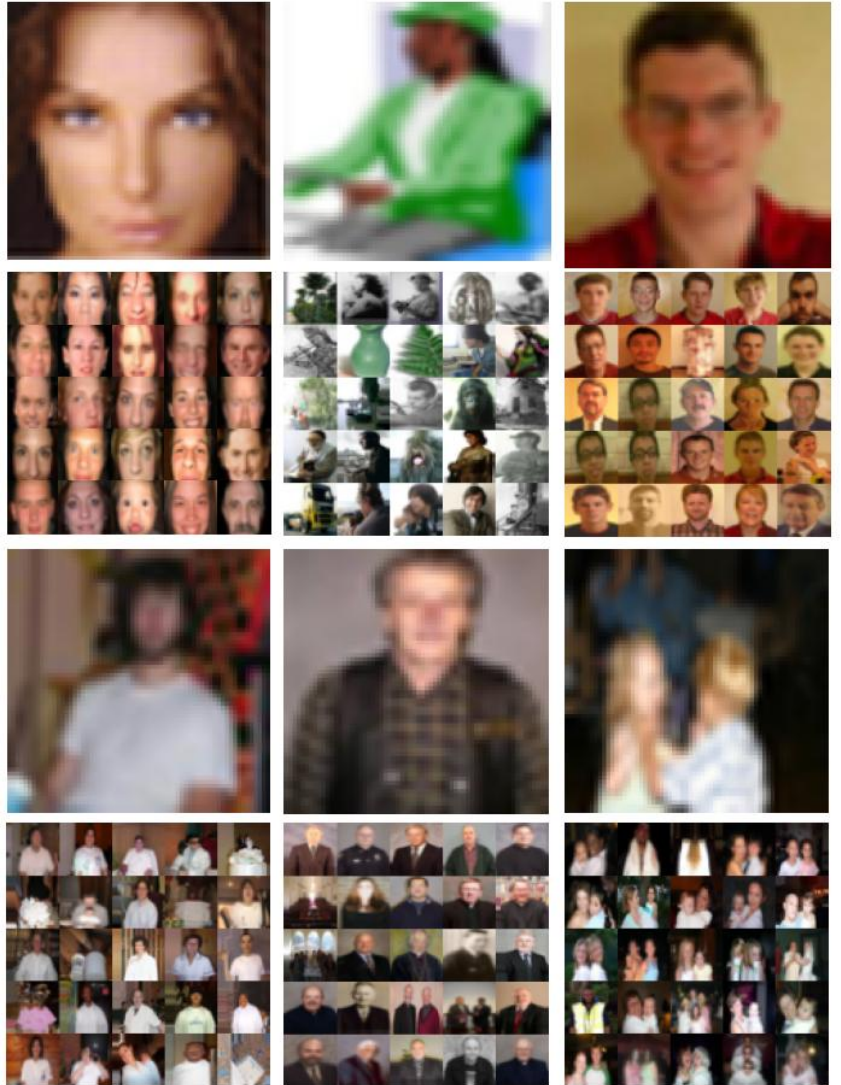


# **Recognition Experiments**



# Person Recognition

- 23% of all images in dataset contain people
- Wide range of poses: not just frontal faces





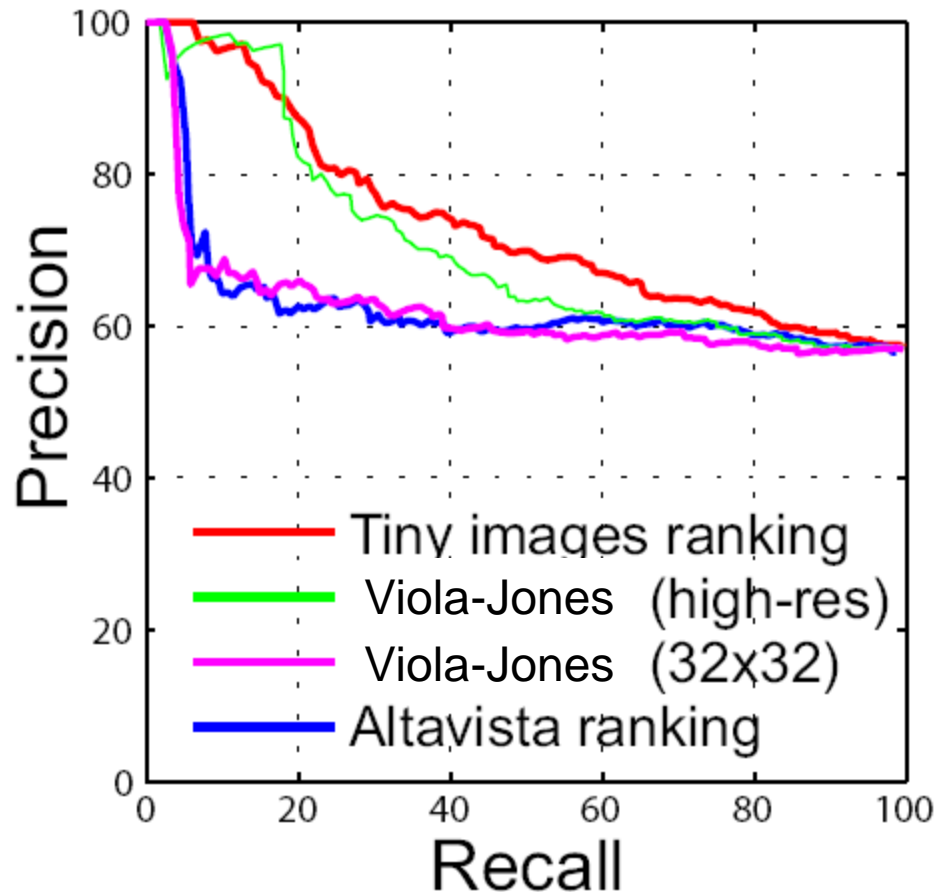
# Person Recognition – Test Set

- 1016 images from Altavista using “person” query
- High res and 32x32 available
- Disjoint from 79 million tiny images



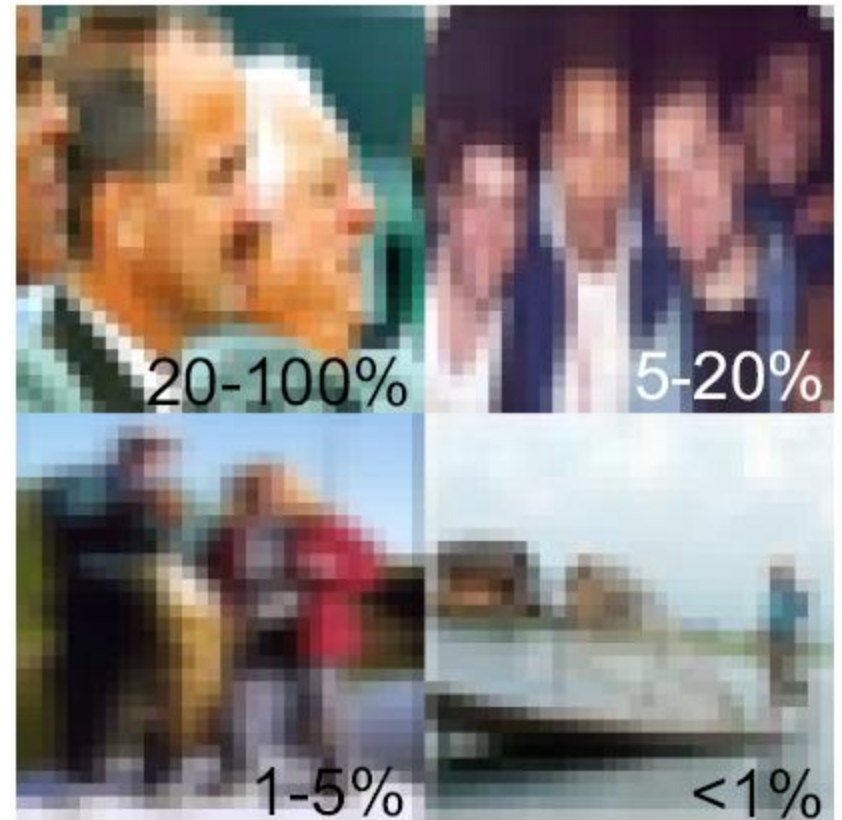
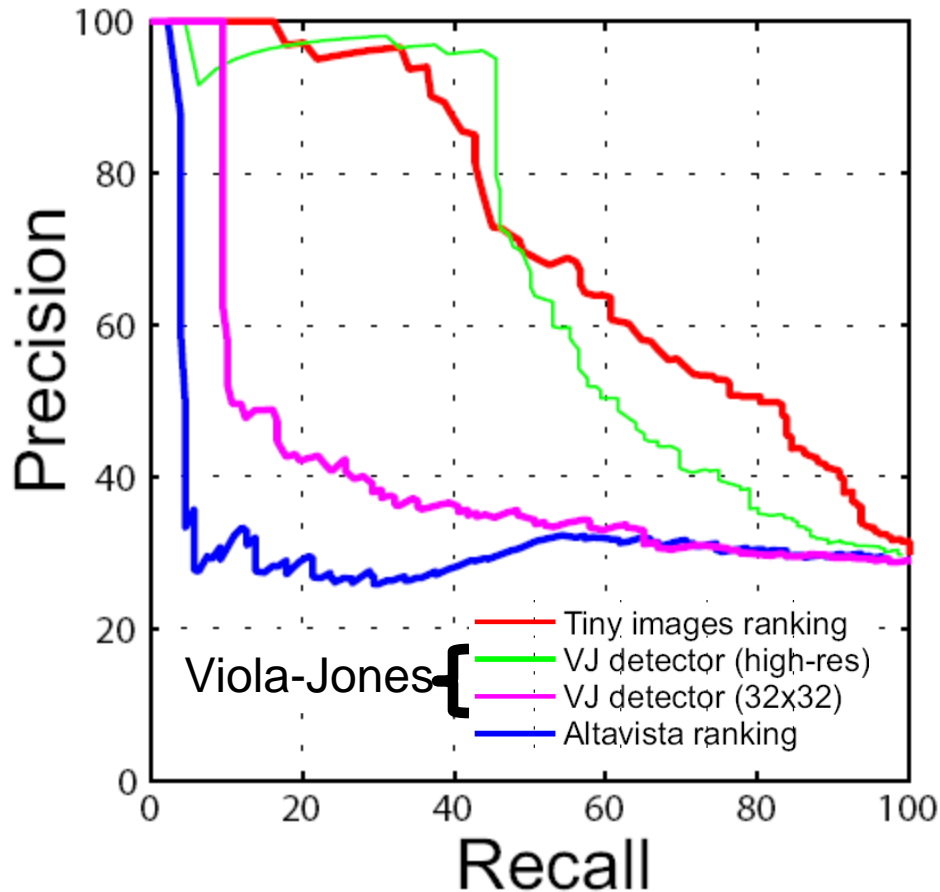
# Person Recognition

- Task: person in image or not?



# Person Recognition

- Subset where face  $>20\%$  of image



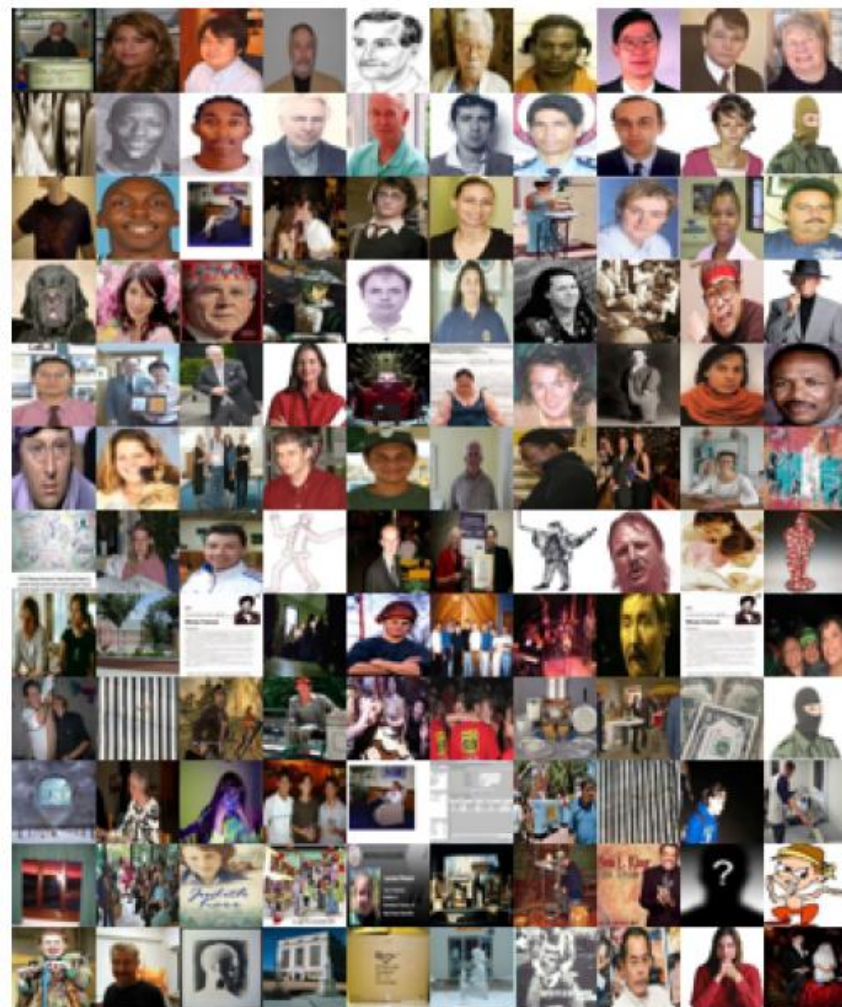


# Re-ranked Altavista Images

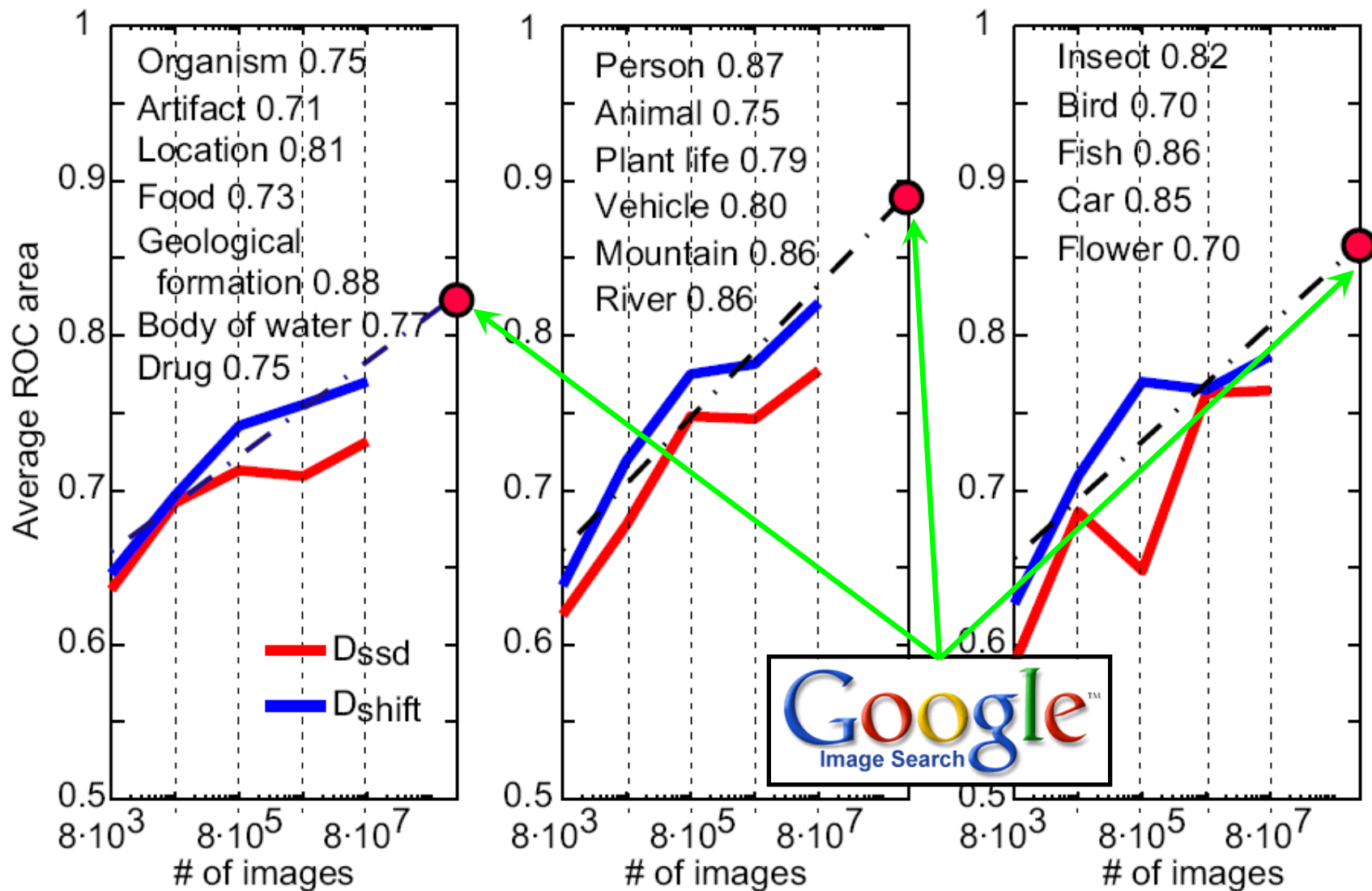
Original



Re-ranked



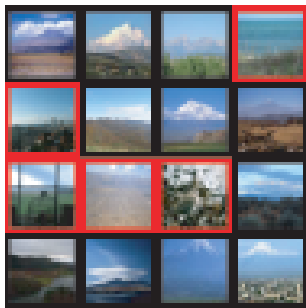
# Object Classification



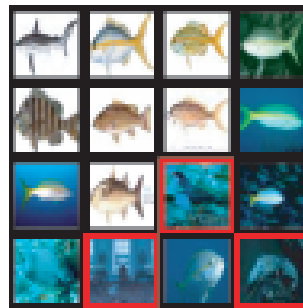
# Object Classification

# images: 7,900 ■ 790,000 ■ 79,000,000 ■

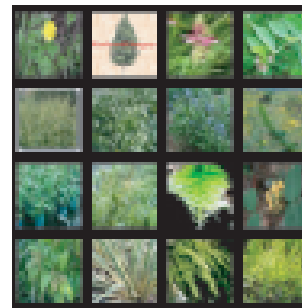
Geological  
formation (32)



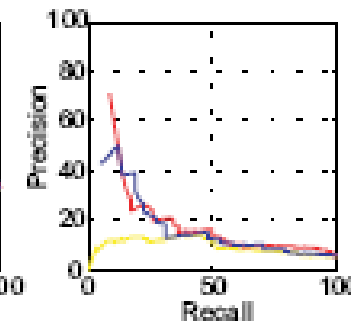
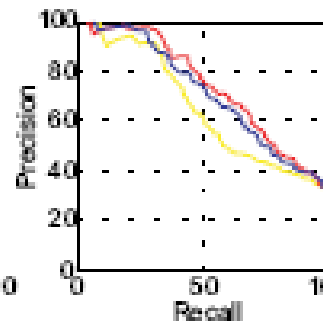
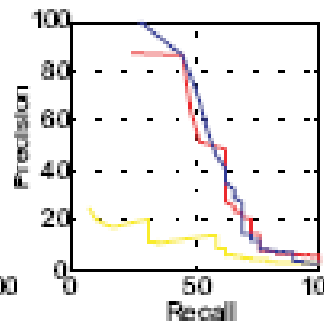
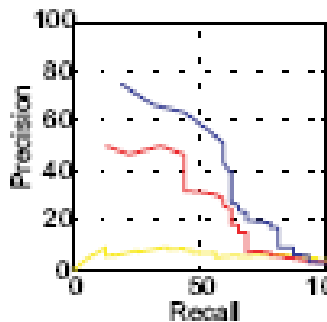
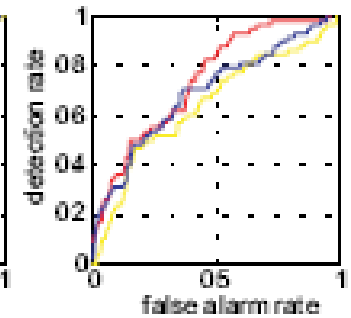
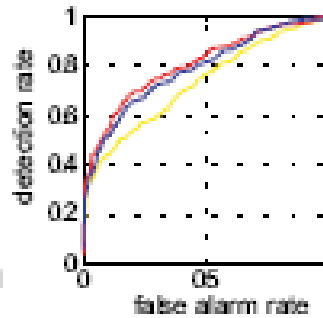
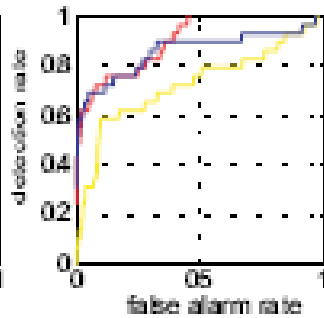
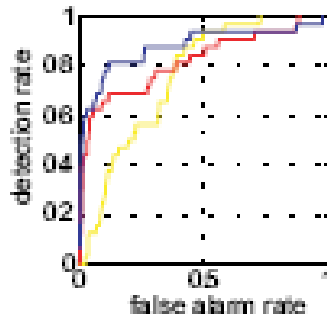
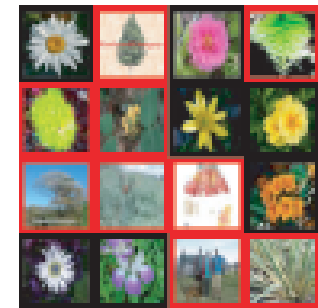
Fish  
(29)



Plant life  
(335)



Flower  
(58)





# **Other Applications**

# Automatic Colorization

Grayscale input  
High resolution

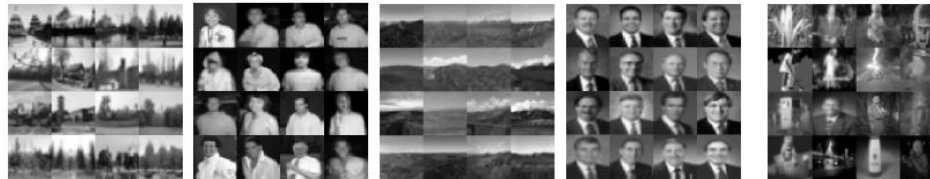


# Automatic Colorization

Grayscale input  
High resolution



Grayscale  
32x32 siblings



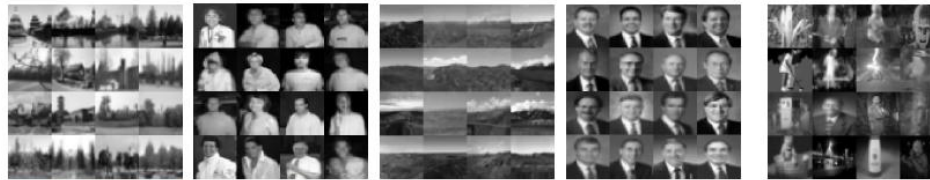


# Automatic Colorization

Grayscale input  
High resolution



Grayscale  
32x32 siblings



Color siblings  
high resolution

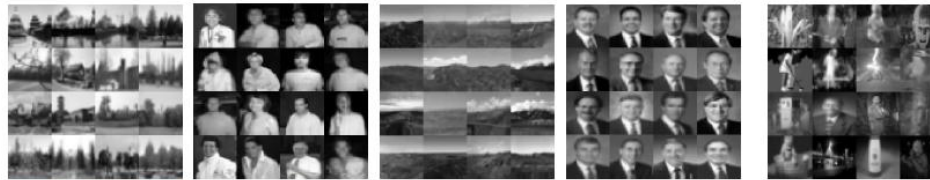


# Automatic Colorization

Grayscale input  
High resolution



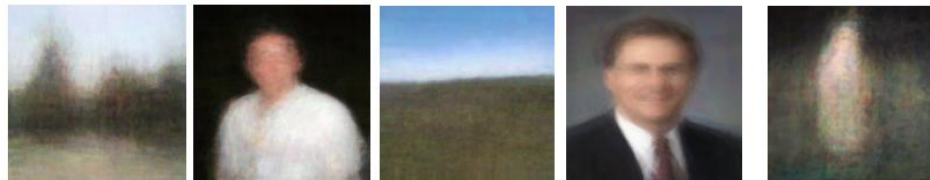
Grayscale  
32x32 siblings



Color siblings  
high resolution



Average of  
color siblings

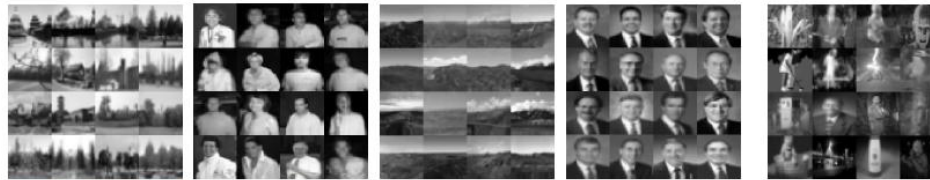


# Automatic Colorization

Grayscale input  
High resolution



Grayscale  
32x32 siblings



Color siblings  
high resolution



Average of  
color siblings



Colorization of input  
using average



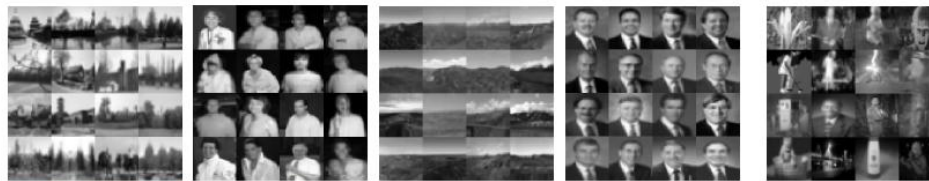


# Automatic Colorization

Grayscale input  
High resolution



Grayscale  
32x32 siblings



Color siblings  
high resolution



Average of  
color siblings



Colorization of input  
using average



Colorization of input  
using specific siblings

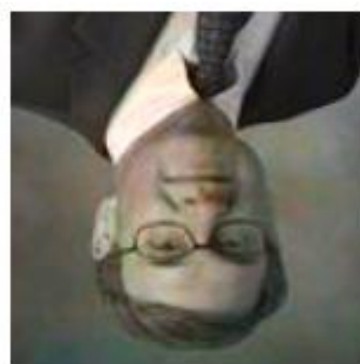


# Automatic Colorization Result

Grayscale input High resolution

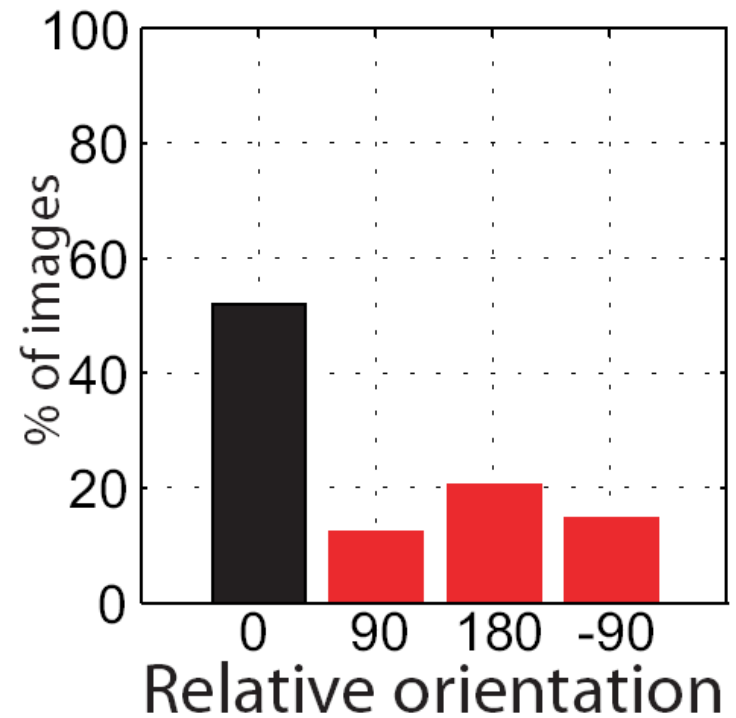
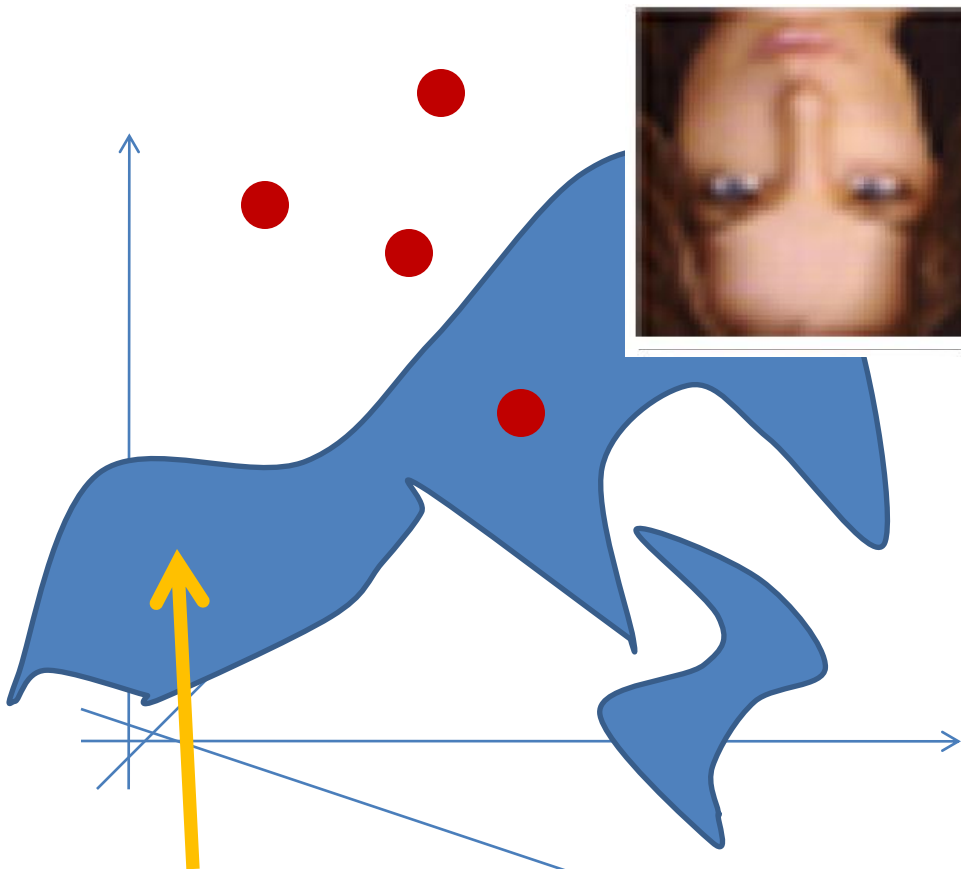


Colorization of input using average



# Automatic Orientation

- Look at mean distance to neighbors

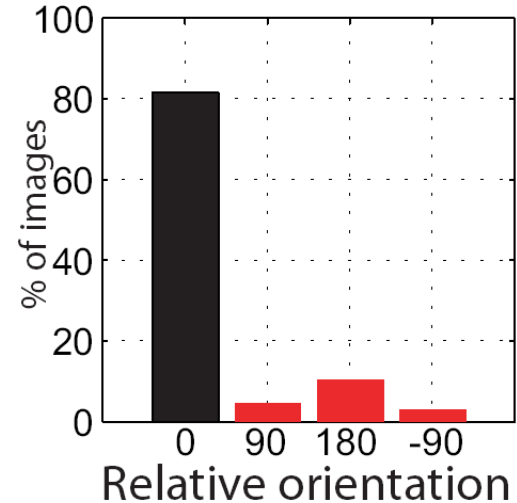


Subspace of natural images



# Automatic Orientation

- Many images have ambiguous orientation
- Look at top 25% by confidence:
- Examples of high and low confidence images:



# Automatic Orientation Examples

0.70



0.64



0.66



0.64



0.86



0.76



0.79



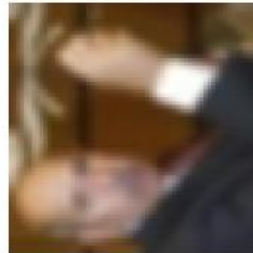
0.77



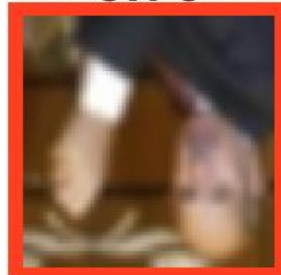
0.66



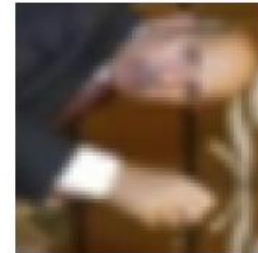
0.62



0.70



0.63



# Related Work

- Hayes & Efros, Scene Completion using Millions of photographs, SIGGRAPH 2007.
- Nister & Stewenius. Scalable recognition with a vocabulary tree, CVPR 2006.
- Hoogs & Collins. Object boundary detection in images using a semantic ontology. In *AAAI, 2006*.
- Barnard et al., Matching words and pictures. *JMLR*, 2003.
- Shakhnarovich et al. Fast pose estimation with parameter sensitive hashing, *ICCV* 2003



# Conclusions



Few Data

Complex Model

- Can get good results simple algorithms & lots of data

Huge amounts of Data

No Model

